ABSTRACT

SANDHU, HARLEEN KAUR. Artificial Intelligence Based Condition Monitoring of Nuclear Piping-Equipment Systems. (Under the direction of Dr. Abhinav Gupta.)

With the resurgence of nuclear energy due to the ever-increasing demand for electricity and carbon free power generation, ensuring safe operations at nuclear power plants (NNPs) is important. Over the past decade, the use of artificial intelligence techniques in the field of health-monitoring has gained significant interest, especially for structures such as buildings and bridges. This dissertation proposes an Artificial Intelligence (AI) framework for the data-driven condition monitoring of nuclear piping-equipment systems, where the vibration response is governed by multiple localized modes unlike that in buildings and bridges. Hence, techniques such as signal processing and pattern recognition are employed to extract degradation-sensitive features. Degradation in piping-equipment systems can occur due to flow-accelerated erosion and corrosion. These locations can potentially exhibit damage such as localized yielding, cyclic fatigue, or initiation of cracking due to an external event such as an earthquake or due to vibrations from normal operating loads such as pump operations. Moreover, such locations can at times go undetected by current inspection techniques. Therefore, this dissertation proposes a framework, which utilizes sensor response to generate an AI database for predicting degraded locations and severity in nuclear piping-equipment systems, in a post-hazard scenario and during normal operations. Degradation severity is classified as minor, moderate, and severe, along with incorporation of uncertainty. Various deep learning algorithms are designed, and their predictive capability is compared. A simple piping system and a safety system from a two-loop reactor plant are considered for the post-hazard scenario, whereas the Z pipe system from EBR II nuclear reactor is investigated for normal operational loads.
Artificial Intelligence Based Condition Monitoring of Nuclear Piping-Equipment Systems

by
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To My family
BIOGRAPHY

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PART I

Introduction
I.1 Introduction

With the invention of artificial intelligence (AI), various fields such as Aerospace, Mechanical and Civil Engineering explore the applicability of deep learning algorithms within structural health-monitoring (SHM) frameworks. In Civil Engineering, machine learning techniques have demonstrated damage detection in structures like bridges, buildings, steel/concrete frames, and buried utility pipelines [1, 2, 3, 4, 5]. This research proposes to investigate the behavior of nuclear piping-equipment systems in order to design a condition monitoring framework using AI based approaches. Such a framework would encompass two distinct aspects. One of them relates to the condition monitoring of safety piping-equipment systems under normal operating loads caused by pump-induced vibrations, flow-induced vibrations, water hammer, etc. The other aspect deals with the condition assessment of the systems after the occurrence of an external hazard. A post-hazard scenario requires a detailed investigation of the system’s degraded state before the nuclear reactor is cleared to restart. An AI guided condition assessment based on the sensor data collected from the system during and/or after the occurrence of an earthquake can be powerful to determine locations with minor, moderate or severe degradation. The diagnosis of the system using a condition assessment framework can be beneficial if current non-destructive testing (NDT) techniques can be implemented at detected degraded locations. It may also help to reduce nuclear power plant (NPP) outage time periods.

The integrity of any nuclear power facility is dependent on the performance of its structures, systems and components (SSCs), like piping-equipment systems which are utilized to carry coolants (water or liquid sodium) to the reactor vessel and steam to the turbine. Thus, substantial resources are allocated towards the maintenance of the piping-equipment safety systems against natural hazards as well as normal operating loads. Over the course of time, the piping-equipment systems of NPPs can experience
degradation due to flow accelerated corrosion and erosion of the system. The phenomena of corrosion and erosion can cause thinning of the pipe walls, which can result in a reduction of the system’s structural strength and stiffness [6]. Piping-equipment systems can also undergo fatigue due to operational vibration loads (caused by fluid flow, pumps, water hammer phenomenon, etc.) and due to thermal cycles. Assessment of fatigue in piping safety systems continues to be a challenging problem. During normal operations, the integrity of piping-equipment systems is expected to be maintained regularly. In a post-hazard situation, nuclear facilities are usually shut down for several months to perform a comprehensive inspection of its safety systems. Under both of these circumstances, an examination of the system’s sensor data or even physical in-person inspection of the systems is necessary. Currently, the nuclear industry utilizes NDT techniques like ultrasound or infrared testing as a part of its condition assessment or maintenance procedures. However, conventional NDT techniques can fail to scan the entire piping-equipment systems and numerous degraded locations can pass undetected. This has caused multiple nuclear SSC failures in the past [6]. Therefore, it is important to identify and retrofit any degraded locations to address the operational functionality of the nuclear piping-equipment systems.

Patterson et al. [7, 8] propose a concept for the digital framework of NPPs in which the importance of SHM and extraction of data using non-destructive inspection techniques, such as vibrational monitoring with real-time sensor data, are emphasized. The concept of vibrational health monitoring is a major component of the proposed research and includes collecting sensor data from the nuclear piping-equipment systems, correlating the sensor data and system’s degraded state, integrating degradation models, and implementing techniques like signal processing, pattern recognition, and feature extraction for degradation detection. Presently, there is a significant emphasis on the development of digital twins (DTs) for the SSCs of nuclear facilities, which requires a robust condition monitoring system. Theoretically, a Digital Twin (DT) serves as a
virtual replica of the power plant’s piping-equipment systems and it integrates the plant’s aging and performance history. The concept of a DT was first introduced in 2003, by Grieses [9], for Product Lifecycle Management (PLM). Since its inception, the DT concept has been applied successfully in various industries, such as space and aircraft, automobiles, production and product design, health care, civil systems and disaster management [10, 11, 12, 13, 14, 15, 16, 17, 18, 19]. The development of a successful DT depends on effective training of the DT utilizing data from real nuclear facilities and their systems. However, access to sensor data from real plants is a very difficult and expensive process that needs to get approval through regulatory agencies. In the proposed research, a proof-of-concept is developed for one component of the DT which relates to the condition monitoring framework using high fidelity simulations for collecting sensor data.

In the past decade, many SHM studies [20, 21, 22, 23, 24, 25, 26, 27] have employed mechanistic models with a characterization of damage indices or data-based AI approaches. The methodologies presented in past studies are dependent on the type of structure being monitored, quality of information carried in the damage indices, and efficiency of feature extraction methods like fast-fourier transform (FFT), power spectral density (PSD), etc. [28, 29, 30]. Damage is detected in civil structures such as buildings and bridges whose behavior is typically dominated by a single mode or very few lower order vibration modes. However, contrary to structures like buildings and bridges, the complex and distributed systems of nuclear equipment and piping often times require multiple low and high frequency vibration modes to characterize its complete response. Consequently, a single damage-sensitive feature may not be able to capture the current degraded state of the system. Thus, the proposed methodology employs a vector of damage-sensitive quantities for nuclear piping system’s diagnostic application.

Furthermore, the existing SHM methodologies developed for buildings and bridges
emphasize on detecting major damage, like cracks and fissures, which initiate only after a significant degradation has occurred. However, the integrity of a nuclear power facility is sensitive to the condition of its SSCs. Significant crack damage can result in nuclear accidents such as loss of coolant scenario. Hence, the health monitoring framework for the safety piping-equipment systems in NPPs should be able to detect locations with any level of degradation including a minor, moderate or severely degraded condition. To detect even minor levels of degradation, this study proposes to incorporate uncertainty in the severity of degradation. While most existing studies focus on detecting degraded locations, the proposed condition assessment framework will be able to detect degradation at certain locations along with a knowledge of their corresponding degradation severities.

The distributed systems of nuclear equipment and piping can generate large amounts of sensor data, making data interpretation the biggest challenge for a condition monitoring framework. The use of artificial neural network (ANNs) and convolutional neural networks (CNNs) as powerful deep learning algorithms is proposed for data handling and processing. Thus, eliminating the need to formulate degradation indices based on structural behavior assumptions. Raw sensor data can be processed and fed into the deep learning algorithms to predict degraded locations and assess the structural life of nuclear piping-equipment systems.

A novel AI driven framework for detection of degraded locations as well as identification of the severity of degradation using vibration data recorded during an external hazard like an earthquake and during normal operations due to pump-operating loads is proposed. FFT, PSD and Short-Time-Fourier-Transform (STFT) feature extraction methods will be explored as vibrational health-monitoring diagnostic quantities of interest for nuclear piping systems. A vector of degradation-sensitive quantities is extracted from sensor data by using traditional signal-processing, pattern recognition and feature extraction methods. For the post-hazard condition assessment,
the architecture and key parameters of an ANN are designed by using a simple piping system as an application case-study. The proposed ANN design along with a sensor placement strategy is tested for a realistic two-loop reactor nuclear piping-equipment system. This two step process helps in illustrating the effectiveness of the proposed data-driven framework. Under normal operating loads, a condition assessment methodology is developed and tested for a piping-equipment system from the EBRII Nuclear Reactor. A condition monitoring framework for nuclear piping-equipment systems can enable safe NPP operations by keeping the operators well informed of the health of nuclear integral safety systems.

I.2 Background

Structural health monitoring is an essential tool to enhance the safety and reliability of structures and systems like bridges, utility pipelines, aircraft wings, nuclear piping-equipment systems, etc., and to reduce the associated maintenance life-cycle costs. For degradation detection applications, non-destructive health assessment techniques utilize the sensor response obtained from the system, when subjected to random vibrations, as the degradation diagnostic tool. However, the principal challenge in vibration-based SHM lies in obtaining a suitable attribute of the system’s response, such as is robust and sensitive to detect minor structural degradation. Feature-extraction techniques can be applied to the sensor response obtained from a nuclear facilities’ SSCs in order to detect degradation in these systems. FFTs and changes in the system’s modal properties have been used as degradation-sensitive features in some past studies [31, 32, 33] to implement an online monitoring strategy. Typically, FFTs and changes in the system’s modal properties are insensitive to minor degradation at degraded locations and their sensitivity to detect degradation can be adversely affected by changes in boundary conditions and sensor locations [34, 35, 36].

The sensor response captured in the time-domain is transformed into its
corresponding frequency-domain using signal processing techniques such as power spectral density (PSD), short-time fourier transform (STFT), wavelet transform (WT) and hilbert-huang transform (HHT). The acquired spectrums are then utilized to extract some degradation-sensitive features or to define damage indices. Martini et. al. [37] propose leak detection in buried plastic pipelines of water supply networks by studying the standard deviation obtained from the sensor response by characterizing a damage detection index called Monitoring Index. A spectrogram of the response is analyzed to investigate the changes in signature due to water leaks. Shinozuka et al. [38] measure the acceleration time-series response in buried water supply pipelines (plastic and metal), to detect pipeline ruptures caused by a change in water pressure. In this study, both time-domain (root-mean-square of the acceleration time-series response) and time-frequency domain features (STFT) are used to detect pipeline rupture by recording dominant frequency shifts. Bao et al. [39] and Rezaei et al. [35] carry out damage detection in pipeline networks by implementing the Hilbert-Huang Transform (HHT) algorithm to define a damage-sensitive index.

Another study by Huang et al. [40] proposes SHM of deepwater risers subjected to vortex induced vibrations, to detect damages like transverse cracks. Frequency response functions (FRFs) are used to derive a new damage index. The use of FRFs requires information on the input excitation load which is usually not available. Ghazali et al. [41] compare the effectiveness of various SHM vibrational techniques (for example, HHT, normalized HHT, Direct Quadrature-DQ, Teager Energy Operator, and Cepstrum analysis) for leak detection in water distribution pipe networks. After comparing the entire frequency-domain spectrums, it is observed that the normalized HHT and DQ algorithms provide best results in detecting damages leading to pipeline leaks. While these studies propose effective damage detection methodologies for pipelines buried in soil or underwater, the vibration response obtained from buried pipe networks is very different from that of nuclear piping-equipment systems. The analysis of pipeline
networks from studies mentioned above requires consideration of boundary conditions due to surrounding soil and fluid, whereas, the piping systems in nuclear facilities are predominantly supported by vertical hangers or mechanical snubbers. As in the case of conventional structures, the methodologies presented in the aforementioned studies are developed to detect cracks and leaks, which are representative of a major damage.

Alamdari et al. [20] define a crack damage-detecting index based on spectral moments obtained from the PSD. In a more recent study, Alamdari et al. [21] propose a similar methodology for detecting cracks in a section of the Sydney Harbor Bridge. Spectral moments are obtained from the sensor response’s PSD. A K-means clustering algorithm is employed to predict cracks in the bridge. In both studies [20, 21], the use of PSD as a damage diagnostic quantity is demonstrated. Another study by Erazo et al. [22] investigates a beam under varying environmental conditions. The Kalman filtering technique is shown to reduce the noise in measured sensor response. Damage is defined as a reduction in stiffness, illustrative of severe cracking and loss of cross-section due to corrosion. A damage index based on PSD spectral moments is specified. In the methodology proposed by the above studies, damage is represented by a unique peak in the PSD response. The technique is quite powerful if the PSD plot contains a single dominant peak as is the case in most structures. The challenge for nuclear piping systems lies in the existence of multiple discrete narrow-banded peaks in the PSD plots of recorded response signal. In addition, minor degradation in nuclear piping systems causes negligible changes in the acquired PSD response.

The computational resources required for data processing can be a challenging component of SHM frameworks. Complex physical systems like nuclear piping, can generate large amounts of sensor data. In order to effectively store, process and extract required features from the acquired sensor data, machine learning approaches can be employed. For instance, ANNs, support vector machines (SVMs), CNNs, fuzzy logic,
k-means clustering and principal component analysis (PCA). In the field of health monitoring, ANNs and CNNs have exhibited numerous advantages including efficient data handling, feature learning, noise handling and parallel computation, as detailed below.

Paulraj et al. [42] propose an ANN for structural steel plate crack damage detection using frequency-domain features, such as the spectral energy values obtained from the discrete Fourier transformation of the acceleration-time series response. Previous studies [1, 2, 23, 24, 43] have employed ANNs along with FRFs and damage indices to detect damage in structures. Lai and Perera [27] use the PSD transmissibility ratio for training a neural network to detect damage severity in a beam structure. The PSD transmissibility ratio is calculated from the acceleration-time-series responses obtained at two different locations on the beam and used to define a normalized damage index for each element. However, the accuracy of the framework to obtain better PSD transmissibility ratios depends on the location of the loading point. In recent years, time-frequency domain features (HHT, wavelet transform and Teager-Huang transform) have been employed as inputs to the ML algorithms [25, 26, 44]. The effectiveness of using time-frequency domain features to detect damage is demonstrated, but processing large amount of data using methods like HHT can be computationally expensive when compared to FFT, PSD and STFT. Moreover, nuclear facilities require real-time data processing and diagnosis of the systems to mitigate accidents. Although considerable work has been conducted on SHM using AI approaches, a lot of the aforementioned studies also focus on detecting significant damage, including cracking, in buildings and bridges.

Some studies [3, 4] have demonstrated the effectiveness of multiple CNNs for each sensor location, by using the complete acceleration-time-series sensor response as the training feature, thereby, eliminating the need to extract any damage-sensitive quantity from the response. CNNs were initially invented for image recognition using 2D image data.
Hence, at their heart, CNNs perform the best for classification of images and computer vision applications. Therefore, CNNs can be trained on the images of acquired acceleration-time series signals to detect structural anomalies in a long-span bridges [45]. In a similar study [46], images from accelerometer sensor data are used for data augmentation and to detect damage in steel jacket-type wind turbine foundations using CNNs. Some studies [47, 48, 49] have explored CNNs for detecting cracks or holes in plate structures. Guided wave imaging, electromagnetic impedance signatures or ultrasonic signals are used to train the CNNs. Another study [50] investigates the role of transmissibility functions and 1D CNNs in detecting damage for a building frame structure along with consideration of white noise in the sensor data. CNNs are also used to create pretrained networks such as Alexnet and ResNet. Some papers [51, 52, 53] utilize the power of such pretrained networks with transfer learning approaches and images obtained from the structural systems (such as cable stayed bridges, towers, concrete structures) to detect damages or for signal denoising.

Although all the above-mentioned studies proposed powerful SHM methodologies to detect damages using CNNs, most of them concentrate on using the entire acceleration-time series signals for 1-D CNNs or on image recognition using 2-D CNNs. However, for piping systems in nuclear power plants (NPPs), enormous sensor data can be generated and it can be difficult to process the complete signals obtained from accelerometer sensors without requiring high computational resources. Therefore, this research explored alternate data preprocessing techniques to detect degradation with minimum computational complexity. Furthermore, it is not always possible to get image data for every location on the piping system that can potentially degrade with time. Therefore, this study also investigates the use of Short-Time Fourier transform (STFT) technique to develop 2-D input data for 2-D CNNs [54].

Piping systems at NPPs are typically subjected to various vibrations during
normal operations. These vibrations can be generated due to attached mechanical parts and their movements, flow-induced vibrations, pressure pulsations, transient phenomenon and multiphase fluid flow such as cavitation, flashing or condensation [55, 56]. Multiple studies in the past have investigated the various sources of vibrations in nuclear piping-equipment systems that can lead to subsequent leakage and failure [57, 58, 59, 60, 61, 62]. A few studies [63, 64, 65, 66, 67] have also proposed methodologies to model such piping vibrations and reduce the cumulative effect on the piping-equipment systems. Most of these studies are focused on flow-induced vibrations that occur due to vortex shedding, flow through valves or nozzles, etc. In nuclear facilities, pumps are required to facilitate numerous essential functions such as transporting coolant from reservoir to the reactor core. Numerous studies have been conducted in the past to characterize the vibrations and flow fluctuations that occur in piping systems due to the use of pumps such as centrifugal [68, 69, 70], reciprocating [71, 72, 73] and electromagnetic [74, 75, 76, 77]. Continuous vibrations over long periods of time can cause fatigue to build up at certain structural discontinuities of the piping-equipment systems. Both high-cycle fatigue and low-cycle fatigue can cause sudden onset of cracks, leakages and breaks in the piping systems, which can eventually lead to a nuclear accident. The phenomenon of fatigue in nuclear piping-equipment systems due to cyclic loads, such as vibrations due to pump operations, has been detailed in past reports and related codes [78, 79, 80, 81]. Significant research has also been conducted on identifying and proposing retrofitting strategies for low-cycle fatigue [82, 83, 84, 85, 86]. However, capturing and preventing high-cycle fatigue that occurs due to pump-induced vibrations remains a challenging area in the design of piping-equipment systems [78]. Therefore, this proposed research aims to enhance the condition monitoring methodology such that can be applied towards preventing high-cycle fatigue in nuclear piping-equipment systems subjected to cyclic loads from pump-induced vibrations.
I.3 Research Objectives

The primary goal of this research is to develop an AI based framework for the condition monitoring of nuclear piping-equipment systems. The proposed framework consists of three distinct objectives:

I.3.1 Objective 1

Design and characterization of an ANN approach for the post-hazard condition assessment of nuclear piping-equipment systems subjected to external hazards.

I.3.2 Objective 2

Design and characterization of an ANN approach for the condition monitoring of nuclear piping-equipment systems under normal operating loads.

I.3.3 Objective 3

Evaluate various deep learning algorithms and assess their relative diagnostic and predictive capabilities for the proposed condition monitoring methodology.

I.4 Proposed Research

The proposed research is divided into three different tasks as explained below. These three tasks are consistent with the research objectives of the dissertation.

I.4.1 Task 1: Post-Hazard Condition Assessment of Nuclear Piping-Equipment systems using ANNs

In this research, a multilayer perceptron (MLP) ANN is utilized to develop a post-hazard condition assessment framework which detects degraded locations and degradation severity in nuclear piping and equipment systems after they are subjected to seismic hazards. A
simple 3-dimensional piping-equipment system is selected as an application case study for developing the proposed approach. Then, a realistic nuclear piping-equipment system is considered for testing the efficacy of the proposed framework. The specific steps undertaken for Task 1 are:

- Develop simulation models for a nuclear piping-equipment system: includes degradation models to represent the degraded state of the system. Assume one degraded location at any given time.
- Automate acquisition of sensor data using a simulation engine: obtain acceleration-time series sensor data.
- Convert the acquired time-domain sensor data into the frequency-domain: evaluate FFT and PSD by assuming the time-domain data to be stationary.
- Incorporate uncertainty in degradation: characterize degradation in 3 different levels: minor, moderate and severe. Incorporate uncertainty in the 3 degradation levels as a uniform distribution with a lower bound and an upper bound at each severity level, i.e., [20%, 30%] for minor, [45%, 55%] for moderate, and [70%, 80%] for severe degradation.
- Implement pattern recognition and design a feature extraction methodology: correlate sensor data and the system’s degraded state. Extract a representative vector of degradation-sensitive features from each sensor’s response. Store the extracted vector in a data repository and utilize it to train the ANN.
- Construct a sensor placement strategy: explore the effects of reduced sensor placement and develop a strategy for the same. In current industry practice, it is impractical to place sensors at numerous locations. Hence, sensor placement strategy is an important component of the proposed framework.
- Develop a MLP ANN: to design a neural network for detecting degraded locations and their severity, investigate the architecture and key parameters of the ANN using the simple piping system configuration.
• Test the proposed approach for a realistic nuclear piping-equipment system: demonstrate the effectiveness of the proposed framework, including feature extraction methodology, ANN design and sensor placement strategy, on the complex safety piping-equipment system of a reactor plant with a two-loop configuration.

I.4.2 Task 2: Artificial Intelligence (AI) Driven Condition Monitoring of Nuclear Piping-Equipment systems under Normal Operating Loads

The equipment and connected piping safety systems of nuclear facilities experience normal operational vibrating loads caused by pump operations, flow-induced, or water hammer phenomenon. This part of the research explores the vibrations in piping-equipment systems due to pump operational loads. The decision to operate the pumps at a certain speed depends on the thermal hydraulic and power generation requirements of the NPP. Therefore, in the case of flow anomalies, different pumps connected to the piping systems can operate at different speeds. The speed of pump operations can determine the amount of vibrations and subsequent fatigue developed in the piping-equipment systems. Cyclic fatigue for prolonged duration of time can cause cracks and leakage in the piping safety systems. At this time, a significant amount of work is being carried out to develop autonomous control systems for NPPs as well as microreactors [87, 88]. One aspect of developing a nearly-autonomous control system is to provide guidance on the constraints on operating the pump at certain speeds that may cause relatively greater fatigue in the piping-equipment system when compared to operating the pump at other speeds. Thus, as a part of the periodic maintenance procedures on piping-equipment system, the proposed condition monitoring framework should be able to:

• Capture and process real-time sensor data.
• Detect degraded locations along with their severity.
• Determine the stress concentrations at detected degraded sections of the system and check it against the allowable ASME design criteria [79].
• Provide a recommendation for safe pump operating speeds.

In the proposed framework, a piping-equipment system is selected from the EBRII nuclear reactor to develop a proof-of-concept for the condition monitoring framework. The piping-equipment system is subjected to vibrational loads due to normal pump operations. The specific tasks undertaken for Task 2 are:

• Develop simulation models for the EBRII nuclear piping-equipment system: study EBRII reactor drawings to create the simulation model [89, 90]. Assume one degraded location at any given time.
• Incorporate the harmonic excitation phenomenon due to pump operational loads: the piping system being considered is connected to the auxiliary pump. Select the speeds for the auxiliary pump’s operation and calculate the frequency of corresponding vibrations imposed on the piping system [87, 88]. For high fidelity simulations, consider multiple harmonic excitation loads by selecting frequency values from the calculated range.
• Similar to the post-hazard condition assessment framework:
  – Automate acquisition of sensor data.
  – Extract a vector of degradation sensitive quantities.
  – Incorporate uncertainty in degradation severity.
  – Utilize the sensor placement strategy developed in Task 1.
  – Use the MLP ANN as designed in Task 1 and test its efficacy against various other ANN architectures and key parameter selections.
  – Detect degraded locations and their corresponding severity levels.
• Design a scenario based recommendation for safe pump operational speeds: generate transmissibility ratio (TR) curves for the stresses developed at the detected degraded
location. Calculate safe TR values from the ASME stress design criteria for nuclear piping systems [79]. Utilize the TR curves to evaluate safe pump operational speeds for the prolonged health of piping systems and to avoid cyclic fatigue hotspots.

I.4.3 Task 3: Assessment of Deep Learning Algorithms for the Condition Monitoring of Nuclear Piping-Equipment Systems

In this research, various deep learning algorithms are evaluated for the proposed condition monitoring framework, in order to assess their relative diagnostic and predictive capabilities. In addition to the performance of AI algorithms, various aspects of data handling are explored such as data collection, processing and extraction, data storage, data assimilation for the deep learning algorithms and the relative computational cost for each of these methods. MLP ANNs are typically used for classification prediction problems trained with time-series data, degradation indices, or a vector of extracted features from the response spectrum. The training data is assigned a class or a label pertaining to a certain classification scheme. Usually, CNNs are used to map images to an output classification or label. They work well for data with some sort of spatial or an order of inter-relationships. For example, text data and images. Nonetheless, CNNs can prove to be beneficial for use with time-series sensor data. CNNs can be designed as one-dimensional or two-dimensional networks, although the 2-D CNN is the most commonly used architecture. To accomplish Task 3, the following steps are undertaken:

- Design MLP ANN and test its efficacy: investigate the architecture and key parameters required to design a MLP ANN. For the training data, use a single degradation sensitive quantity versus a vector of degradation-sensitive features extracted from the sensor’s acquired response.
- Design a 1-D CNN and test its efficacy: investigate the architecture and key parameters required to design a 1-D CNN. For the training data, use a vector of
degradation-sensitive features extracted from the sensor response.

- Design a 2-D CNN and test its efficacy: investigate the architecture and key parameters required to design a 2-D CNN. Transform the acceleration-time-series sensor response using STFT to obtain a 2-D array containing the energy of the response versus the corresponding frequency and time. Use obtained 2-D STFT sensor data to train the 2-D CNN.

- Compare the diagnostic capability exhibited by each of the above-mentioned algorithms.

I.5 Organization

This dissertation primarily consists of five parts. Part I gives an introduction to the problem being studied followed by a discussion of the objective of the research. The second Part of the dissertation presents a post-hazard condition assessment of nuclear piping-equipment systems using ANNs. The third Part focuses on the AI driven condition monitoring of nuclear piping-equipment systems under normal operating loads. In the fourth Part, an assessment of deep learning algorithms for the proposed condition monitoring framework is conducted. Finally, the fifth Part of this dissertation presents a summary and conclusions of the work that has been discussed in Part II, Part III, and Part IV. It also proposes recommendations for future work.
PART II

Post-Hazard Condition Assessment of Nuclear Piping-Equipment systems using Artificial Neural Networks
II.1 Introduction

Safety of nuclear power plants (NPPs) is dependent upon the integrity of their structures, systems and components (SSCs). Piping-equipment systems carry coolants (such as water) to the reactor vessel and steam to the turbine. Consequently, the nuclear industry spends significant time and resources to maintain the structural integrity and functionality of such safety systems. In the case of an external event such as a major earthquake, nuclear plants are typically shut down and a very detailed assessment of the plant’s safety systems is performed before it can be cleared for restart. In most cases, such an assessment spans several months. Therefore, a condition monitoring framework utilizing sensor data collected from the systems can be helpful in providing information about the degraded locations in the system. This paper focuses on the vibration-based condition monitoring of nuclear piping-equipment systems using artificial neural networks to facilitate post-hazard assessment.

Previous studies [20, 21, 22, 23, 24, 25, 26, 27] in the field of health monitoring of structures rely either on mechanistic models or incorporate data-based artificial intelligence (AI) approaches. Studies which rely on mechanistic models often characterize a damage index to detect damage in the system. Some AI based approaches also employ a damage index to train machine learning algorithms. The accuracy of damage detection depends on the sensitivity exhibited by these damage indices and feature extraction methods such as fast-fourier transform (FFT) or power spectral density (PSD) [29, 30, 36]. Almost all the existing health monitoring studies that explore the role of AI are focused on applications in civil structures such as buildings and bridges. In contrast to these structures, nuclear piping-equipment behave as complex distributed systems. Unlike buildings and bridges in which a single mode or very few lower order vibration modes are sufficient to characterize the response quantities of interest, multiple low and high frequency vibration modes are required to characterize the complete response of
piping-equipment systems. Therefore, instead of a single damage-sensitive feature, it would be much more appropriate to use a vector of damage-sensitive quantities for the diagnostic training of an artificial neural network (ANN) model.

Another limitation of extending the existing applications in buildings and bridges to the piping-equipment systems relates to the objective of existing studies that is focused on detecting cracks (damage) in structural systems. Typically, damage such as cracking initiates only after a significant degradation has occurred. The piping-equipment systems in NPPs cannot afford to reach a stage of significant degradation as a loss of coolant due to cracking can result in a nuclear accident. Therefore, the primary objective in the health monitoring of piping-equipment systems in NPPs is to detect not just the locations with severe degradation but also those with minor and moderate levels of degradation. Detecting locations with minor degradation is also dependent on the uncertainty of degradation severity. It is important to note that most existing studies focus on detecting damaged locations only, and do not include detection of damage severity. A post-hazard assessment requires detection of the level of degradation along with the degraded locations so that all locations with minor or moderate degradation may be eliminated from additional detailed assessments.

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 [6]. 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 current practice, NPPs use expensive non-destructive testing (NDT) techniques like ultrasound
or infrared testing to detect such degradation in the systems. 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 [6]. Therefore, it is quite critical to identify and retrofit such degraded locations in advance of a major crack and potential leakage scenario.

The research proposed here explores a novel data-driven framework for detection of degraded locations as well as identification of the severity of degradation at each degraded location using vibration data recorded during an earthquake. To develop a robust condition monitoring framework, data from real nuclear plants should be used. However, access to sensor data from real plants is a very difficult and expensive process that needs to get approval through regulatory agencies. In order to use accurate data from a plant, a proof-of-concept needs to be demonstrated to ensure that any new methodology gives reasonably good results. Such a proof-of-concept requires two steps. The first step is to develop an analytical proof of concept using high fidelity simulations. The second step requires verification and validation of the framework using an experimental program to further enhance the initial developed methodology. The proposed research is focused on the very first step of development of the framework and proof of concept using high fidelity simulations. The next phase of experimental validation is currently being studied and will be published later.

This manuscript explored the use of FFT and PSD as vibrational health-monitoring diagnostic quantities of interest for nuclear piping systems, evaluates the relative benefits of utilizing these quantities and suggests alternatives based on the lessons learned from this study. A methodology for signal-processing, pattern recognition and feature extraction is designed to generate a vector of degradation-sensitive quantities from acquired sensor data. While ANNs are a useful tool for structural health 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 ANN architecture and characterize its key parameters. Then, the proposed design is tested by application to a more complex and realistic nuclear piping-equipment system. This two step process helps in illustrating the effectiveness of the proposed data-driven framework. The predictive capability of ANNs depends on the quality of sensor data and the efficiency achieved through sensor placement. Once again, a two step process is used such that the simple piping system is utilized to establish a sensor placement strategy and it is then applied to the piping-equipment system of a two-loop reactor plant. Furthermore, the effect of uncertainties in the degree of degradation is also investigated. The proposed methodology can predict not only degraded locations, but also identify the severity level when categorized as minor, moderate or severe. 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.

II.2 Existing Studies

Many health monitoring techniques used in power plants utilize the vibration response obtained from structures, systems and components (SSCs). However, the principal challenge lies in obtaining a suitable attribute of the system’s response that is robust and sensitive to detect minor structural degradation. A few studies [31, 32, 33] implement an online monitoring strategy which utilizes FFTs and changes in the system’s modal properties to detect damage. These are effective in detecting damage in conventional structures, where the primary response of the structure is contained within the first few lower order modes of vibration. On the other hand, in piping systems, the response is dominated by multiple modes of vibration in both low and high frequency regions. Furthermore, a piping system can experience degradation at numerous locations
simultaneously. Although features such as FFTs and changes in the system’s modal properties are easier to extract and process, they are insensitive to minor degradation and are also very sensitive to changes in boundary conditions and sensor locations [34, 35, 36].

Martini et. al. [37] propose leak detection in buried plastic pipelines of water supply networks by studying the standard deviation obtained from the sensor response and characterizing a damage detection index called Monitoring Index. A spectrogram of the response is analyzed to investigate the changes in signature due to water leaks. Bao et al. [39] and Rezaei et al. [35] carry out damage detection in pipeline networks by implementing the Hilbert-Huang Transform (HHT) algorithm to define a damage-sensitive index. These studies propose effective damage detection methodologies for pipelines buried in soil or underwater. The analysis of such buried pipelines requires consideration of boundary conditions due to surrounding soil and fluid, unlike the piping systems in nuclear facilities, which are predominantly supported by vertical hangers or mechanical snubbers. Therefore, the vibration response obtained from such buried pipelines is different than the response obtained from piping systems in NPPs. As in the case of conventional structures, the methodologies proposed in the aforementioned studies are developed to detect cracks and leaks, which are representative of a major damage.

Based on previous studies [20, 21, 22], it appears that power spectral density (PSD) can be a powerful degradation-diagnostic quantity due to computational efficiency and its sensitivity to minor degradation. A PSD describes the distribution of power over the frequency-domain for a time-series response. Alamdari et al. [20] define a crack damage-detecting index based on spectral moments obtained from the PSD. In a more recent study, Alamdari et al. [21] propose a similar methodology for detecting cracks in a section of the Sydney Harbor Bridge. Spectral moments are obtained from the sensor response’s PSD. A K-means clustering algorithm is employed to predict cracks in the bridge. In
both these studies [20, 21], the use of PSD as a powerful damage diagnostic quantity is demonstrated. Another study by Erazo et al. [22] investigates a beam under varying environmental conditions. The Kalman filtering technique is shown to reduce the noise in measured sensor response. Damage is defined as a reduction in stiffness, illustrative of severe cracking and loss of cross-section due to corrosion. A damage index based on PSD spectral moments is specified. In the above mentioned studies, damage is represented by a unique peak in the PSD response. The technique is quite powerful if the PSD plot contains a single dominant peak as is the case in most structures. The challenge for nuclear piping systems lies in the existence of multiple discrete narrow-banded peaks in the PSD plots of recorded response signal. In addition, minor degradation in nuclear piping systems causes negligible changes in the PSD response.

The structural health assessment of complex physical systems requires processing large amounts of data to extract degradation-sensitive features. 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 years [91, 92, 93, 94, 95, 96]. In the field of health monitoring, ANNs and CNNs have exhibited numerous advantages such as efficient data handling, feature learning, noise handling and parallel computation. Previous studies [1, 2, 23, 24, 43] have employed ANNs along with frequency response functions (FRFs) and damage indices to detect damage in structures. The use of FRFs requires information on the input excitation load which is usually not available. Some studies [3, 4] have demonstrated the effectiveness of CNNs by using the complete acceleration-time-series sensor response as the training feature, thereby, eliminating the need to extract any damage-sensitive quantity from the response. However, in complex systems such as nuclear piping, enormous computational resources will be required to process the complete acceleration-time-series responses at all desired locations. In recent
years, time-frequency domain features (such as HHT, wavelet transform and Teager-Huang transform) have been employed as inputs to the ML algorithms [25, 26, 44]. These studies demonstrate the effectiveness of time-frequency domain features, but processing large amount of data using methods like HHT can be computationally expensive when compared to FFT and PSD.

**II.3 Description of the Problem**

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. 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 [97, 98, 99, 100, 101, 102]. 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, a methodology is developed to train the AI algorithm for detecting degraded locations and their severity following any major earthquake. The AI network is trained over the response obtained from the piping system, which is subjected to several real and simulated earthquakes. Then, the designed AI network is tested using the degraded system’s response against an unknown earthquake. Sensor data collected from the piping-equipment system subjected to seismic loads is in the form of an acceleration-time-series response such as is representative of the sensor data that can be acquired from accelerometers installed on the system in a real nuclear plant. The proposed monitoring framework is demonstrated on two different nuclear piping-equipment systems. First, a simple piping system is considered so that it allows for an easier interpretation of the results. Next, the condition assessment framework is applied to an actual two-loop reactor piping system. The simple piping-equipment system selected for the first case study is
quite similar, but not identical, to a USNRC piping benchmark problem [103].

II.3.1 Case Study 1: Simple Piping-Equipment System

For the first case study, a three-dimensional piping-equipment system is selected and a corresponding finite element (FE) model is created. This system consists of three straight-pipe elements, two bend-pipe elbow elements contained between two fixed anchors and a hanger support as shown in Figure II.1.

![Simple Piping System](image)

Figure II.1: Simple Piping System

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. In the event of an earthquake, interpreting sensor data to detect degraded locations is important for identifying locations of potential damage or cracking and initiating any mitigation strategy to prevent a loss of coolant accident. To generate the training database of sensor data, a collection of 100 real and synthetic earthquake input records is considered. A time-dependent earthquake time history analysis is conducted for each record. The damping ratio for the piping system
is taken as 5%, and the acceleration-time-series response at each of the nodes in the FE model is captured. The sensitivity of the network’s predictions to sensor locations is explored in section II.5. Each sensor collects the response data 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. As illustrated in Figure II.1, the FE model consists of total nine nodes that can be used as potential sensor locations and subsequent degradation-sensitive feature extraction.

II.3.2 System Degradation

Flow-accelerated corrosion and erosion can cause thinning of the pipe walls or a loss of cross-section in piping systems as well as a reduction in Young’s modulus [6]. Thus, the phenomena of erosion and corrosion cause a reduction in the stiffness of the system. The change in the stiffness 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, degradation is quantified by a reduction in the thickness of pipe-walls of the piping elements. From previous studies [97, 98, 99, 100, 101, 102], it is observed that degradation usually takes place at the nozzles (anchors), elbows and T-joints of a piping system. Here, degradation is assumed to take place at one of the following locations:

- Nozzle node 1
- Elbow nodes 3 and 5
- Elbow nodes 7 and 9

For simplicity, degradation is instantiated at these locations, one at a time. 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 an uncertainty in the degree of degradation. Therefore, uncertainty is incorporated in the proposed framework and described in the following section.

II.3.3 Uncertainty in 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, a 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 should account for an uncertainty by considering a distribution for the degradation severity. This study assumes a uniform distribution with a lower bound and an upper bound to model the uncertainty in degradation at each severity level, i.e., [20%, 30%] for minor, [45%, 55%] for moderate, and [70%, 80%] for severe degradation. Then, a Monte-Carlo simulation is used to generate random severity values for each degradation classification and these values are employed to collect a training database for the ANN.

II.3.4 Signal processing

The time-series response (sensor data) collected from the piping system is processed to extract degradation-sensitive features. In this study, the power spectral density is explored as a potentially robust diagnostic quantity. PSD can be defined as the energy (or power) contained in a time-series response. If the time-series response is stationary in nature, and its FFT exists, $X(f)$, then its PSD is calculated as the magnitude squared of the
FFT of the time-series response, as shown in Equation II.1.

\[ PSD(f) = |X(f)|^2 \]  

(II.1)

The PSD 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 [20, 22] also define damage indices based on these values. In this research, the maximum PSD value is used as the degradation-sensitive feature. It is also assumed that the response/signal is stationary in nature, such that its FFT exists, over a short period of time. Figure II.2 illustrates a typical acceleration-time-series sensor response and its corresponding PSD in the frequency-domain.

Figure II.2: Signal Processing of Sensor Response

II.4 Characterization of Artificial Neural Networks

II.4.1 Overview of Deep Learning: Artificial Neural Networks

Machine-learning techniques have been employed for structural health monitoring applications in building and bridges [43, 104, 105]. This paper explores deep learning techniques for the health 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. The basic unit of an ANN is a single neuron as shown in Figure II.3. It consists of an input and output connected together by an activation function. Weighted inputs, $w_ia_i$, are summed up with a bias term, $b$, and transmitted through the activation function, $f$, to obtain the output, as shown in Equation II.2. Activation functions are used to “activate” a neuron if its data is relevant for model prediction [106]. Nonlinear activation functions such as sigmoid, tanH, ReLU, softmax etc., are used so that multiple neuron layers can be assembled to create a deep neural network, which is necessary to accurately analyze complex sensor data.

$$\text{Output} = f\left(\sum_{i=1}^{n}(w_ia_i) + b\right) = f(w_1a_1 + w_2a_2 + \ldots + w_na_n + b) \quad (\text{II.2})$$

Figure II.3: Single Neuron

A collection of such neurons creates an ANN, which can solve a wide range of problems such as damage and degradation prediction, pattern recognition, computer vision and classification. A typical ANN structure consists of an input layer, a single or more hidden layers and an output layer. Each layer can have different number of neurons and each neuron behaves as an independent data processing unit. After the initial weights for the input layer have been defined, a forward propagation is performed to make an initial output prediction. The error function calculates the difference between the predicted value and the true value. In order to optimize the input weights, such that the error function yields a small quantity, a backpropagation algorithm is used [107]. A single layer feed-forward artificial neural network, known as the multi-layer perceptron (MLP), is shown in Figure II.4.
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 changes 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 simple piping system is used to characterize and assess these parameters, details of which are proposed in Section II.5. Although ANNs have become widely popular for health monitoring applications, they require large amounts of sample data to be trained effectively. Once all the aforementioned aspects of an ANN have been investigated, the algorithm can be used for inverse problems with high precision. The
proposed methodology explores the use of an MLP artificial neural network for condition assessment of nuclear piping-equipment systems.

II.4.2 Initial Implementation of ANN

Based on the simple piping system shown in Figure II.1, various ANN parameters are examined and an initial implementation of the ANN, with parameter values as illustrated in Table II.1, is selected.

<table>
<thead>
<tr>
<th>Table II.1: ANN Training Parameters</th>
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<tbody>
<tr>
<td><strong>Parameter</strong></td>
</tr>
<tr>
<td>No. of hidden layers</td>
</tr>
<tr>
<td>Total no. of neurons</td>
</tr>
<tr>
<td>Optimizer</td>
</tr>
<tr>
<td>Epochs</td>
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<tr>
<td>Learning Rate</td>
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<tr>
<td>Batch Size</td>
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<tr>
<td>Dropout</td>
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<tr>
<td>Activation Functions</td>
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<tr>
<td>Validation split</td>
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</tbody>
</table>

These parameters are described in further detail below:

- **Optimizer**: Neural networks train on the provided input data to minimize the loss obtained from comparing the output value predictions against the target results. Optimizers are utilized to minimize these losses obtained from mathematical expressions called loss functions. Various optimization algorithms such as Stochastic Gradient Descent (SGD), Adaptive Moment (Adam), Root Mean Square Propagation (RMSProp), Adaptive Gradient (AdaGrad), etc., can be
implemented. In this study, Adam optimizer is selected for the MLP neural network because of its ability to handle large datasets with computational efficiency [108]. Adam combines optimization concepts from both SGD with momentum and RMSProp algorithms as shown in Equation II.3 and Equation II.4.

\[
W_{t+1} = W_t - \eta_t' V_{dW_t} \tag{II.3}
\]

where,

\[
\eta_t' = \frac{\eta}{\sqrt{S_{dW_t} + \varepsilon}}
\]

\[
V_{dW_t} = \beta_1 V_{dW_{t-1}} + (1 - \beta_1) \left( \frac{\partial C}{\partial W_{t-1}} \right)
\]

\[
S_{dW_t} = \beta_2 S_{dW_{t-1}} + (1 - \beta_2) \left( \frac{\partial C}{\partial W_{t-1}} \right)^2
\]

\[
b_{t+1} = b_t - \eta_t' V_{db_t} \tag{II.4}
\]

where,

\[
\eta_t' = \frac{\eta}{\sqrt{S_{db_t} + \varepsilon}}
\]

\[
V_{db_t} = \beta_1 V_{db_{t-1}} + (1 - \beta_1) \left( \frac{\partial C}{\partial b_{t-1}} \right)
\]

\[
S_{db_t} = \beta_2 S_{db_{t-1}} + (1 - \beta_2) \left( \frac{\partial C}{\partial b_{t-1}} \right)^2
\]

Given that, \( \eta \) is the initial learning rate and \( \eta_t' \) is the dynamic learning rate, \( \varepsilon \) is added to avoid division by zero error, \( V_{dW_t} \) and \( V_{db_t} \) are the exponential averages of gradients as defined by SGD with momentum, \( S_{dW_t} \) and \( S_{db_t} \) are the exponential averages of squared gradients as defined by RMSProp.

- **Epochs:** The neural network algorithm learns with each forward and backward pass of the network’s calculations, known as an epoch. Depending on the problem being solved, hundred to thousand epochs may be used to obtain a stable model. A low number of epochs can result in underfitting the problem whereas a high
number of epochs may result in overfitting. 2000 epochs are used to obtain an optimal model architecture. In order to prevent overfitting, early stopping criteria is included wherein the algorithm stops training if the model does not improve its performance after a certain number of epochs.

- **Learning rate**: The speed at which the model “learns” is called the learning rate. A very small learning rate would take the network a very long time to obtain optimal parameters and thus, would result in a failure to train the network. On the other hand, a very high learning rate would generate an unstable neural network by getting stuck at sub-optimal parameters during training. The value of learning rate can be chosen between 0 and 1. For the initial implementation, a value of 0.001 is used.

- **Batch size**: In order to increase the computational efficiency of the network, data is fed to the network in small batches of 16. The size of batches refers to the total number of data samples that will be propagated through the neural network and it can affect the efficiency of the ANN. Using large batch sizes can result in quicker training of the model, however, the model may not be able to efficiently generalize new data. The concept of batch size is different from that of an epoch. If a total of 500 data points are available for training, and a batch size of 10 is selected, each epoch will train over 50 batches.

- **Dropout**: Dropout is a computationally cheap regularization method that is specified to tackle the problem of overfitting the data. It helps the network to randomly “drop” some values during the training so that the algorithm does not overfit the data. In this initial model of the neural network, a dropout of 0.5 is selected for the hidden layer.

- **Activation function**: PReLU (Parametric Rectified Linear Unit) is used to activate neurons in the hidden layers, and softmax is used for the output layer. PReLU is an activation function that is derived from ReLU (Rectified Linear
ReLU is a nonlinear activation function that can be used for activating the hidden layers of deep neural network models [109]. The main advantage of ReLU over other nonlinear activation functions such as sigmoid and hyperbolic tangent is that it does not suffer from the problem of vanishing gradient [110]. For a positive input value, ReLU returns the exact same value and for input values of 0 or lesser, ReLU returns a value of 0 (Figure II.5a). PReLU builds upon this concept by returning a non-zero value for inputs that are 0 or lesser (Figure II.5b) [111]. As shown in Equation II.5, the activation function of PReLU multiples all negative values with a small factor, $\alpha_i$, that can be learned by the neural network during training of the model.

\[
PReLU(z_i) = \begin{cases} 
  z_i, & \text{if } z_i > 0 \\
  \alpha_i z_i, & \text{if } z_i \leq 0 
\end{cases} \tag{II.5}
\]

For problems with binary or multi-class classification using neural networks, softmax activation function yields a probabilistic distribution over the target classifications.
In Equation II.6, it is shown that the softmax for any input vector $z$ and its $i^{th}$ value $z_i$ can be calculated by normalizing the exponential function applied to $z_i$ over a total of $K$ number of classes.

$$softmax(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_i}} \quad (II.6)$$

In the case of neural networks, the output layer receives a score for each classification level from the hidden layers. The softmax function converts these scores into a probabilistic distribution and a classification with the highest value of probability is assigned a value of 1 whereas others are assigned a value of 0. For example, if the output layer receives a score of $z = [2, 4.5, 9, 1, 5.1]$, then the obtained probabilistic distribution can be plotted as shown in Figure II.6. With the highest probability of 0.97 obtained for the third value of 9 from the score vector $z$, a classification vector of $[0, 0, 1, 0, 0]$ would be achieved for this example.

- **Validation**: Validation is carried out by creating a split in the training data set in order to design a best fit neural network model for the problem at hand. 30% of the training data is used for validation and subsequent hyper-parameter tuning as detailed in Section II.5. Using validation techniques can also help identify if the model is overfitting the training data.
In this study, a collection of 100 earthquake ground motions are used for FE simulations, and three degradation severity levels with uncertainty are introduced at 5 locations in the piping system. A total of 4,500 simulations are conducted as a part of the proposed research. Approximately 70% of the simulations are used for training and 30% are used for testing the neural network’s prediction capabilities. For the initial part of the research, all nodes from the FE model of the piping system are selected as triaxial sensor locations. The effect of reduced sensors and sensor placement is proposed in Section II.5. The time-series sensor data obtained as acceleration-time-series data, is transformed into the frequency domain to generate the corresponding fast-fourier transform (FFT) and power spectral density (PSD). The maximum FFT ($FFT_{max}$) and PSD ($PSD_{max}$) values are extracted from each sensor’s response acquired from the degraded system. Therefore, 27 such values are extracted for FFT and PSD from the nine triaxial sensor responses. Each FE simulation results in a 27 point vector as a one-dimensional training array, which is then fed into the developed ANN as illustrated in Figure II.4. The input layer consists of 27 neurons representing the triaxial response collected from 9 sensor locations.
The output layer consists of 5 neurons representing the 5 potential degraded locations in the piping-equipment system. The results obtained from the initial implementation of the ANN using $FFT_{\text{max}}$ and $PSD_{\text{max}}$ as degradation-sensitive features are tabulated in Table II.2

<table>
<thead>
<tr>
<th>Degradation-Sensitive Feature</th>
<th>Testing accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>$FFT_{\text{max}}$</td>
<td>41%</td>
</tr>
<tr>
<td>$PSD_{\text{max}}$</td>
<td>45%</td>
</tr>
</tbody>
</table>

The results from the initial implementation show that the ANN based on the use of $FFT_{\text{max}}$ and $PSD_{\text{max}}$ is unable to predict degraded locations with desired accuracy. It illustrates that the initial simple implementation of ANN is not learning sufficient information from the extracted features. Since the PSD is obtained from squaring the magnitude of the FFT, the difference in comparing maximum values between the degraded and non-degraded state using PSD versus FFT is also squared. This concept is detailed in Equation II.7, where $PSD_0$ and $PSD_1$ is the maximum PSD magnitude from non-degraded and degraded response respectively, and $X_0$ and $X_1$ is the maximum FFT magnitude from non-degraded and degraded response respectively.

$$PSD_0 = X_0^2 \quad \text{and} \quad PSD_1 = X_1^2 \quad \text{from Equation II.1}$$

$$X_\Delta = \text{abs}(X_0 - X_1)$$

$$PSD_\Delta = \text{abs}(PSD_0 - PSD_1) = \text{abs}(X_0^2 - X_1^2)$$

Now, $x + y > 1$ for all real numbers $x, y > 1$

$$\implies (x + y)\text{abs}(x - y) > \text{abs}(x - y)$$
\[ \Rightarrow \quad \text{abs}(x^2 - y^2) > \text{abs}(x - y) \]

\[ \therefore \quad \text{abs}(X_0^2 - X_1^2) > \text{abs}(X_0 - X_1) \quad \text{for all} \quad PSD_0, PSD_1, X_0, X_1 > 1 \quad (II.7) \]

For majority of the acquired sensor responses from the piping-equipment systems, the value of $PSD_0, PSD_1, X_0, X_1$ will be greater than 1. Therefore, using $PSD_{max}$ generates slightly better results than the $FFT_{max}$ as the ANN is able to learn from higher values of $PSD_\Delta$ as compared to $X_\Delta$. For the next part of this study, PSD is further explored as the degradation-sensitive training feature. Enhancement of the proposed framework using pattern recognition and feature extraction, studying the architecture of the ANN in detail, and implementing reduced sensor placement is carried out and demonstrated in Section II.5.

**II.5 Proposed Enhancement**

**II.5.1 Pattern Recognition and Feature extraction**

In the initial implementation described above, the maximum value from the PSD ($PSD_{max}$) response is collected to train the ANN and a 45% prediction accuracy is achieved. The performance of an ANN depends on the quality of the degradation-sensitive training feature. $PSD_{max}$ and derived damage indices have worked well to detect damage in structures such as building and bridges [20, 21, 22] in which one or few first order modes influence the response of the structure. However, in the case of distributed piping systems, multiple modes contribute to the response at any location in the piping system. Typically, $PSD_{max}$ corresponds to what may be considered as one of the significant modes. A degradation at a given location may not change the sensor data significantly for that specific mode. Therefore, it is difficult to identify which mode or modes will be impacted the most by degradation. Some studies consider the response
from multiple modes to derive the damage indices [23, 25, 26, 27]. However, the value of the damage index can be governed by the highest response quantity from one mode. Contribution of lower order modes can be lost by considering a single damage index. Pattern recognition, using the complete time-series signal, can be a suitable candidate to detect changes in the response. However, such an approach is computationally inefficient.

In the study described below, 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. Therefore, to overcome this challenge where minor degradation causes no changes in the maximum PSD value, an enhancement has been proposed. In order 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. Pattern recognition is implemented and it is observed that the maximum difference in the PSD response may or may not occur at the maximum PSD value, as shown in Figure II.7.
The approach proposed in this manuscript collects PSD values at certain significant peaks, which are defined as all peaks within 20% of the maximum PSD value. Once the significant peak PSD values are collected from both the degraded and the non-degraded response, the corresponding differences are calculated and the maximum difference ($\Delta_{\text{max}} PSD$) is extracted as the degradation-sensitive feature using Equation II.8 and Equation II.9. In addition, the corresponding frequency ($\omega_\Delta$) at which the maximum PSD difference occurs is extracted. The PSD value from the non-degraded response ($PSD_{0,\Delta}$) corresponding to the frequency $\omega_\Delta$ is also saved. 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 II.3.
Table II.3: Feature Extraction for a Vector with Four Quantities of Interest

<table>
<thead>
<tr>
<th>QoIs</th>
<th>Definition</th>
<th>Sample Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$PSD_{max}$</td>
<td>Maximum PSD amplitude from degraded response</td>
<td>3.1E + 05</td>
</tr>
<tr>
<td>$\Delta_{max}PSD$</td>
<td>Maximum difference observed in significant PSD peaks</td>
<td>3%</td>
</tr>
<tr>
<td>$\omega_\Delta$</td>
<td>Frequency corresponding to $\Delta_{max}PSD$</td>
<td>17 Hz</td>
</tr>
<tr>
<td>$PSD_{0,\Delta}$</td>
<td>non-degraded PSD peak corresponding to $\omega_\Delta$</td>
<td>2.8E + 05</td>
</tr>
</tbody>
</table>

The value of frequency is an essential component of the degradation detection framework that has been explored in this paper. Between various degraded locations in the system, the frequency ($\omega_\Delta$) corresponding to the maximum difference in PSD response ($\Delta_{max}PSD$) can change due to degradation. During pattern recognition, it is observed that a degradation in the piping-equipment system does not induce any noticeable frequency shift at the peak PSD values. Thus, the framework compares the PSD response values at the same frequency. 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.

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

$$\Delta_{max}PSD = \max|\Delta_{peak_i}PSD|$$

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.
With the new approach, four quantities of interest per sensor response are fed into the ANN model. In order to appropriately utilize the power of a vector of quantities extracted from the sensor data, Artificial Intelligence (AI) approaches, such as ANNs, can be very effective. ANNs can help in eliminating the need to manually correlate the various degradation-sensitive quantities with the degraded state of the system.

II.5.2 Architecture of the ANN

In this study, a multilayer perceptron (MLP) ANN is developed for detecting the degradation in piping-equipment system. One of the components that governs the performance of a traditional neural network is its architecture. In order to design a robust network, the performance of the proposed framework to the architecture of the ANN is investigated. Four different neural networks are built with varying number of hidden of layers and parameters such as the batch size and learning rate (Table II.4).

As a part of the proposed research, hyper-parameter training is conducted to examine the accuracy of various values for:

- Learning rate of the model: 0.001, 0.005, 0.01
- Batch size of the input data: 8, 16, 32

The models are trained over 2000 epochs for all the possible hyper-parameter combinations, and the validation accuracy obtained from each of these ANNs is tabulated in Table II.5.
Table II.4: Various ANN architectures

<table>
<thead>
<tr>
<th>Design Components</th>
<th>Design 1</th>
<th>Design 2</th>
<th>Design 3</th>
<th>Design 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Figure II.4)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hidden Layers</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>No. of hidden</td>
<td>36</td>
<td>32</td>
<td>64</td>
<td>96</td>
</tr>
<tr>
<td>neurons</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>64</td>
<td>64</td>
<td>96</td>
<td>128</td>
</tr>
</tbody>
</table>

Table II.5: Validation Accuracy for ANN Design

<table>
<thead>
<tr>
<th>Batch Size</th>
<th>Learning Rate</th>
<th>Validation Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>8</td>
<td>0.001</td>
<td>89%  95%  96%  96%</td>
</tr>
<tr>
<td></td>
<td>0.005</td>
<td>77%  86%  86%  86%</td>
</tr>
<tr>
<td></td>
<td>0.01</td>
<td>68%  82%  75%  83%</td>
</tr>
<tr>
<td>16</td>
<td>0.001</td>
<td>90%  95%  <strong>97%</strong>  96%</td>
</tr>
<tr>
<td></td>
<td>0.005</td>
<td>83%  87%  90%  91%</td>
</tr>
<tr>
<td></td>
<td>0.01</td>
<td>73%  78%  85%  89%</td>
</tr>
<tr>
<td>32</td>
<td>0.001</td>
<td>92%  96%  96%  96%</td>
</tr>
<tr>
<td></td>
<td>0.005</td>
<td>83%  92%  93%  95%</td>
</tr>
<tr>
<td></td>
<td>0.01</td>
<td>76%  87%  85%  81%</td>
</tr>
</tbody>
</table>

Computationally, all the four 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 results with batch size of 16 and a learning rate of 0.001. The plots for hyper-parameter tuning on the training accuracy, validation accuracy, training loss and validation loss against the number of epochs are shown in Figure II.8. Various dropout values are also tested within the 3 hidden layer neural network architecture, as shown in Table II.6. A dropout of 0.5 is selected for the last hidden layer to avoid overfitting with lower dropout values and loss of training data with higher dropouts.

Table II.6: Hyper-parameter tuning of Dropout

<table>
<thead>
<tr>
<th>Dropout</th>
<th>Validation Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>98%</td>
</tr>
<tr>
<td>0.3</td>
<td>98%</td>
</tr>
<tr>
<td>0.5</td>
<td>97%</td>
</tr>
<tr>
<td>0.9</td>
<td>96%</td>
</tr>
</tbody>
</table>

A training accuracy of 98% and a validation accuracy of 97% is achieved by implementing a deep neural network with three hidden layers. Therefore, the parameter values are determined as mentioned in Table II.1, but with updated three hidden layers and a total of 192 neurons in the hidden layers. After finalizing the architecture of the proposed ANN, data is extracted from the repository 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.
II.5.3 Sensor Placement

In order to reduce computational costs while maintaining a certain level of accuracy, optimal sensor placement is necessary. In real structures, it is not feasible to put sensors at
all locations. Hence, the proposed study examines the effect of sensor placement. Significant data is required to train an ANN and the quality of information contained in the training features governs the performance of the ANN model. The use of a vector of degradation-sensitive quantities enriches the quality of information in the training data. In order to lower the computational cost, the number of sensors employed on the piping-equipment system must be reduced. 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. The simple pipe model considered in this study has a vertical span of 9 ft. and two horizontal spans of 3 ft. each. For studying the effects of sensor placement, four sensors are considered to be located at the two elbows of the piping-equipment system, as shown in Figure II.9. The straight pipe spans are relatively short and therefore no sensor is placed on those spans.

![Figure II.9: Sensor Optimization](image)

From each triaxial sensor response, the PSD is generated and a vector of four degradation-sensitive quantities is extracted. Finally, a two-dimensional training array containing the degradation-sensitive vector from each sensor response is fed into the ANN, as shown in Table II.7 and Figure II.10. The input layer of the ANN consists of 12 neurons representing the triaxial response collected from 4 sensor locations, and rest of the network’s architecture is kept same as before.
The complete data repository is divided into training data (approximately 70%) and testing data (approximately 30%). After extracting degradation-sensitive information from the sensor data and training the designed deep neural network with reduced sensors, a 96% accuracy in predicting degraded locations is achieved. Even with reduced sensor
placements, the artificial neural network is able to predict degraded locations satisfactorily. An additional study is conducted to illustrate the effects of varying number of sensors on the error generated while testing the ANN model. In Figure II.11, it is observed that a high number of sensors results in lowest errors, whereas a low number of sensors can cause insufficient training of the ANN.

![Figure II.11: Effects of varying sensors on the ANN Model Errors](image)

It is found that the four elbow sensors are the most sensitive to the degraded state of the system. An optimal number of sensors, such as the four sensors used in this study, can reduce computational and economic costs of installing numerous sensors whilst maintaining the integrity of the condition assessment framework.

II.5.4 Predicting Degradation Severity

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 in particular, identify degradation as minor versus moderate or major. Therefore, to predict degraded locations as well as their severity levels, the proposed approach is extended to incorporate this objective. The architecture of the ANN, as shown in Figure II.12, is modified to include 15 neurons in the output layer, where each neuron represents the five potential degraded locations
along with the corresponding level of degradation severity as minor, moderate or severe.
The proposed ANN model achieved a testing accuracy of 96%. Thus, it is observed that
the proposed ANN can detect degraded locations as well as degradation severity with
high prediction accuracy, as shown in Table II.8.

Table II.8: Accuracy of Proposed Condition Assessment Framework

<table>
<thead>
<tr>
<th>ANN Model</th>
<th>Predict Locations</th>
<th>Predict Locations and Severity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Hidden Layer</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9 Sensors</td>
<td>45%</td>
<td>-</td>
</tr>
<tr>
<td>1 QoI</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 Hidden Layers</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9 Sensors</td>
<td>97%</td>
<td>97%</td>
</tr>
<tr>
<td>4 QoIs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 Hidden Layers</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 Sensors</td>
<td>96%</td>
<td>96%</td>
</tr>
<tr>
<td>4 QoIs</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*QoI: Quantity of interest*
II.6  Application of Proposed Enhanced Framework

II.6.1  Case Study 2: Primary system of a Two-Loop Reactor Plant

The framework developed in previous sections is applied to a three-dimensional multi-branched piping-equipment system, in order to illustrate the effectiveness of the proposed condition assessment framework. 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 II.13 [103].
Finite element simulations are carried out to generate sensor data. Since degradation usually occurs at nozzles (anchors), elbows and T-joints, it is instantiated at these locations of the complex piping-equipment system as mentioned below [97, 98, 99, 100, 101, 102].

- Hot leg and cold leg connections at the reactor pressure vessel nozzles
- Input and output nozzles of the pump
- Elbows of the piping system connecting pumps and steam generators

Ten sensors located at elbows, nozzles and long straight spans of about 15 ft., are considered from the same reactor loop as the degraded locations. The system is subjected to a collection of 100 earthquake records, and the acceleration-time-series response is obtained from the sensor locations. In a manner similar to the first case study, uncertainty in the severity of degradation is incorporated in the finite element simulations. A total of 5,400 simulations are conducted as a part of this study. The acceleration-time-series sensor response is converted to power spectral density, and a vector of degradation-sensitive quantities is extracted to create a machine learning database. The artificial neural network
developed using the simple piping system described in case study 1 is employed for the complex piping-equipment system and its corresponding database containing degradation-sensitive features. The results for predicting degraded locations and their severity levels are tabulated in Table II.9. These prediction results illustrate the effectiveness of the proposed framework in monitoring degradation locations in nuclear piping-equipment systems. 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.

<table>
<thead>
<tr>
<th>ANN Model</th>
<th>Predict Locations</th>
<th>Predict Locations and Severity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Hidden Layer</td>
<td>10 Sensors</td>
<td>14%</td>
</tr>
<tr>
<td>1 QoI</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 Hidden Layers</td>
<td>10 Sensors</td>
<td>99%</td>
</tr>
<tr>
<td>4 QoIs</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*QoI: Quantity of interest

II.7 Summary and Conclusions

A major earthquake at a nuclear power plant requires a careful and detailed assessment of the structural integrity of plant’s SSCs. This study is aimed at creating an artificial intelligence driven framework for the condition assessment of nuclear equipment and piping. A simple 3-dimensional piping-equipment system is selected as an application case study for developing the proposed approach. The sensor response is converted from
an acceleration-time series signal to its power spectral density (PSD). It is shown that PSD is a powerful diagnostic quantity for detecting all levels of degradation, including minor degradation, in complex distributed systems. It contains information about the system’s current state and corresponding dynamic characteristics. Then, a realistic nuclear piping-equipment system is considered for testing the efficacy of the framework proposed in this research. It is observed that high levels of accuracy at 99% can be achieved in predicting the degraded locations as well as the severity levels. The key conclusions of the study are summarized as follows:

- The applicability of physics-based models can be sensitive to the type of structure/system being monitored. Considering a single damage index as the degradation-detection feature can result in a loss of response from lower order modes of vibration in piping systems. For nuclear piping-equipment systems, pattern recognition is necessary to extract optimum information from the sensor data. It is shown that using only one quantity of interest, such as the maximum peak PSD value, results in an inadequate diagnostic database as the contribution to the response from multiple modes of interest may be lost. 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 are extracted.

- The effects of sensor placement are studied for the simple pipe system and a strategy is developed. The effectiveness of the proposed sensor placement strategy is illustrated by applying it to the complex piping-equipment system. It is observed that the quality of data obtained after reducing the number of sensors is still sufficient for training the ANN framework. Studying the effects of sensor placement can be beneficial in reducing computational and economic costs incurred due to large amounts of data-processing from numerous triaxial sensors.

- The proposed condition assessment framework is able to detect degraded locations
along with the severity in degradation as minor, moderate or severe. Detecting cracks in nuclear systems is representative of major damage which can lead to nuclear accidents. Hence, detection of minor degradation in such systems can be quite effective. This study also incorporates uncertainty in the degradation severity levels to illustrate that the assessment framework is quite effective even when such uncertainties are present.

- Deep learning algorithms can be extremely helpful in processing a vector of degradation-sensitive features extracted from the sensor data. After training and testing the architecture and various key parameters for the deep learning algorithms, significant accuracy is achieved in predicting potential degraded locations as well as degradation severity in the simple piping system. To check the efficacy of the proposed ANN framework, it is applied to a reactor coolant loop piping-equipment systems and a 99% accuracy is achieved in detecting degradation locations and the corresponding severity levels.

It is shown that with the help of modern AI techniques and data processing, degradation in distributed systems, such as nuclear equipment and piping systems, can be monitored efficiently. While this study is quite preliminary and exploratory in nature, it provides a strong foundation for enhancing it further and for potentially testing it using actual measured sensor data.
PART III

AI Based Condition Monitoring of Nuclear Piping-Equipment Systems Subjected to Normal Operating Loads
III.1 Introduction

Operations and maintenance costs comprise about 60 to 70% of the overall generating cost in legacy light water nuclear power plants [113]. The current practice involves performing maintenance of safety systems through performance trending and maintenance practices, and of passive components through aging management programs [114]. In many plants, non-destructive testing (NDT) techniques like ultrasound or thermal imaging are used to collect the data on structures, systems and components (SSCs) degradation only during outage. However, this data collection is not comprehensive as sometimes it is not possible to conduct conventional NDT techniques for scanning the entire system due to time constraints, shutdown of the plant and subsequent loss of revenue. Due to these constrains, degraded locations may pass undetected, and may cause multiple nuclear SSC failures [6]. Therefore, it is important to identify and retrofit any degraded locations to address the operational functionality of the nuclear safety systems. In recent years, condition monitoring frameworks based on Artificial intelligence (AI) has gained significant attention. An AI guided condition monitoring based on the sensor data collected from the system in real-time can be powerful to determine the degraded locations and their severity. The diagnosis of safety systems such as piping-equipment systems using a condition monitoring framework can be beneficial if current NDT techniques can be first implemented at detected degraded locations. It may also help to reduce nuclear power plant (NPP) outage time periods.

Currently, the nuclear industry is encouraging significant research [115, 116, 117, 118, 119, 120, 121, 122] towards developing autonomous control systems for NPPs as well as advanced nuclear reactors. The primary goal of an autonomous control system is to provide recommendations to the operator during normal operations as well as beyond design basis events by developing a digital twin of the nuclear reactor using artificial intelligence techniques [87, 88]. A condition monitoring framework for nuclear piping-
safety systems is an important component of any autonomous management and control system for nuclear reactors. One aspect of developing a nearly-autonomous control system is to provide guidance on the constraints on operating the pump at certain speeds that may cause relatively greater fatigue in the piping-equipment system when compared to operating the pump at other speeds. Thus, a condition monitoring framework with the enhanced ability to provide recommendations on pump operational speeds can prove to be an important aspect of autonomous nuclear reactor control systems.

Over the years, piping systems in a NPP can undergo degradation due to flow-assisted corrosion particularly at T-joints, elbows, or nozzles. The degradation is measured in terms of thinning of the pipe walls and this causes the reduction in the stiffness and thereby the reduction in the structural strength of the piping system [6]. With time, degraded elements in the piping system can become potential hot-spots for fatigue build up. This can cause sudden failure in the form of cracking and leakage in the piping system. In engineering practice, it is common for equipment and connected piping systems to experience vibrations due to operational loads [123]. The nuclear piping-equipment systems can be subject to cyclic fatigue due to operational vibration loads (caused by fluid flow, pumps, water hammer phenomenon, etc.) and due to thermal cycles [78]. Assessment of fatigue in piping safety systems continues to be a challenging problem as the piping elements do not exhibit any physical changes due to fatigue. Therefore, it is difficult to detect the progression of cyclic fatigue with advanced techniques of nondestructive testing or scans. However, with an AI based condition monitoring framework that utilizes sensor data from the piping-equipment systems, the potential hot-spot locations for fatigue build-up can be detected at an earlier stage. Furthermore, comparing the stresses developed in the piping-equipment systems due to operational vibration loads against the design fatigue curves criteria as mentioned in the ASME BPVC II [79] can provide strategic assessments, such as safe pump speeds and allowable number of cycles, to the maintenance operators.
The concept of vibrational health monitoring is a major component of the proposed research and includes collecting sensor data from the nuclear piping-equipment systems, correlating the sensor data and system’s degraded state, integrating degradation models, and executing signal processing, pattern recognition and feature extraction for degradation detection. The development of a successful SHM or condition monitoring methodology depends on effective training of the framework utilizing data from real nuclear facilities and their systems. However, access to sensor data from real plants is a difficult and expensive process that needs to get approval through regulatory agencies. In the proposed research, a proof-of-concept is developed which relates to the condition monitoring framework using high fidelity simulations for collecting sensor data.

Part II of the dissertation highlights the limitations of extending existing health monitoring studies [20, 21, 22, 35, 37, 91, 92, 93, 94, 95, 96] conducted for civil structures such as buildings and bridges to piping-equipment systems. These previously proposed methodologies, though powerful for their respective applications, cannot be applied for developing a condition monitoring framework for nuclear piping-equipment systems because of the difference in the acquired sensor response and dynamic characteristics. The proposed methodology in Part II employs a vector of damage-sensitive quantities for the nuclear piping system’s diagnostic application, to detect locations with their corresponding level of degradation including a minor, moderate or severely degraded condition. The distributed systems of nuclear equipment and piping can generate large amounts of sensor data, making data interpretation the biggest challenge for a condition monitoring framework. The use of artificial neural network (ANNs) and convolutional neural networks (CNNs) as powerful deep learning algorithms is proposed for data handling and processing. Thus, eliminating the need to formulate degradation indices based on structural behavior assumptions. Raw sensor data can be processed and fed into the deep learning algorithms to predict degraded locations and assess the structural life of nuclear piping-equipment systems.
While Part II is focused on developing a condition monitoring framework for nuclear safety systems subjected to external hazards, the research presented in Part III focuses on applying the concepts proposed in Part II and extending the condition monitoring framework application for nuclear equipment-piping systems subjected to normal operating loads. An equipment-piping system is selected from the EBRII Nuclear Reactor and a proof-of-concept is developed wherein the proposed framework utilizes data collected from sensors to generate a machine learning data repository. The effect of operational pump vibrations on the equipment-piping system is analyzed by conducting high fidelity simulations and generating sensor data. Degradation is quantified as a reduction in the thickness of piping elements, thereby causing a reduction in the structural stiffness. The severity of degradation is classified as minor, moderate and severe along with uncertainty in the severity levels. The signal processing, pattern recognition and feature extraction approaches proposed in Part II of this dissertation are applied to the EBRII piping system and a vector of damage-sensitive quantities is extracted for training the ANN model.

Part III of the dissertation focuses on three important aspects: (i) the sensor data generated for piping-equipment systems subjected to vibrational loads can be different from the data generated in a post-hazard scenario. Usually, the power spectrum acquired from sensor responses against harmonic vibrational loads is smoother and contains very few peaks when compared to the power spectrum acquired from sensor responses against seismic loads. Therefore, the proposed condition monitoring framework with its vector of degradation sensitive quantities is implemented for equipment-piping systems subjected to normal operating vibrations. (ii) The results predicted by the proposed monitoring framework are studied even further by conducting a thorough investigation into the cases that are predicted erroneously for degraded locations as well as the severity levels. (iii) Additionally, a strategy based-assessment methodology for recommending “safe” pump operational speeds to avoid high-cycle fatigue build up in the nuclear piping systems is
proposed which can be beneficial to the maintenance operators. Continuous condition monitoring of such systems would result in lowering the maintenance costs along with extending the operating lifetime for a nuclear power plant.

III.2 Literature Review

Structural health monitoring is an essential tool to enhance the safety and reliability of structures and systems like bridges, utility pipelines, aircraft wings, nuclear piping-equipment systems, etc., and to reduce the associated maintenance life-cycle costs. For degradation detection applications, non-destructive health assessment techniques utilize the sensor response obtained from the system, when subjected to random vibrations, as the degradation diagnostic tool. However, the predominant challenge in vibration-based SHM lies in obtaining a suitable attribute of the system’s response, such as is robust and sensitive to detect minor structural degradation. Feature-extraction techniques can be applied to the sensor response obtained from a nuclear facilities’ SSCs in order to detect degradation in these systems. FFTs and changes in the system’s modal properties have been used as degradation-sensitive features in some past studies [31, 32, 33] to implement an online monitoring strategy. Typically, FFTs and changes in the system’s modal properties are insensitive to minor degradation and their sensitivity to detect degradation can be adversely affected by changes in boundary conditions and sensor locations [34, 35, 36].

For health and condition monitoring of systems, the sensor response captured in the time-domain is transformed into its corresponding frequency-domain using signal processing techniques such as power spectral density (PSD), short-time fourier transform (STFT), wavelet transform (WT), hilbert-huang transform (HHT), etc. The acquired spectrums are then utilized to extract some degradation-sensitive features or to define damage indices. Some past studies [35, 37, 38, 39, 41] characterize damage indices from the acquired sensor response and spectrum analysis to detect cracks and leakages in buried
utility pipeline networks. Another study by Huang et al. [40] proposes SHM of deepwater risers subjected to vortex induced vibrations, to detect damages like transverse cracks. Frequency response functions (FRFs) are used to derive a new damage index. The use of FRFs requires information on the input excitation load which is usually not available. While these studies propose effective damage detection methodologies for pipelines buried in soil or underwater, the vibration response obtained from buried pipe networks is very different from that of nuclear piping-equipment systems. The piping systems in NPPs are typically supported by snubbers or vertical hangers, whereas the buried pipeline networks from existing studies requires consideration from the type of surrounding fluid or soil in their analysis. Furthermore, majority of the existing studies have developed monitoring methodologies to detect cracks or leakages as the damage in the system. However, for nuclear systems, cracks signify major damage and a nuclear facility cannot afford to reach the stage of cracks and leakage in the system, as it can cause accidents such as loss of coolant in the power plant.

A few previous studies [20, 21, 22, 27] have also explored the capability of power spectral density (PSD) and derived damage indices as a damage-sensitive quantity for bridges and a beam under varying environmental conditions. The damage in the structure is captured as a unique peak in the PSD plot of the acquired sensor response. These existing techniques are powerful in their application towards structures whose PSD response would contain a single peak representing damage. However, for nuclear piping-equipment systems, minor degradation can cause minute changes in the PSD response, as cannot be captured easily without a robust condition monitoring framework with AI capabilities.

The computational resources required for data processing can be a challenging component of SHM frameworks. Complex physical systems like nuclear piping, can generate large amounts of sensor data. In order to effectively store, process and extract required features from the acquired sensor data, machine learning approaches such as
ANNs, support vector machines (SVMs), CNNs, fuzzy logic, k-means clustering and principal component analysis (PCA) can be employed [25, 26, 44, 91, 92, 93, 94, 95, 96]. Some studies [1, 2, 23, 24, 42, 43] have demonstrated the use of ANNs for detection of crack damage in structural systems whereas others [3, 4] have formulated techniques based on CNNs for each sensor’s acceleration-time series response. However, for nuclear piping systems, the use of multiple CNNs with large amounts of time-series sensor data can quickly result in extensive computational costs. Nuclear facilities require real-time data processing and diagnosis of the systems to mitigate accidents. Although considerable work has been conducted on SHM using AI approaches, a lot of the aforementioned studies also focus on detecting significant damage, including cracking, in buildings and bridges.

Piping systems at NPPs are typically subjected to various vibrations during normal operations. These vibrations can be generated due to attached mechanical parts and their movements, flow-induced vibrations, pressure pulsations, transient phenomenon and multiphase fluid flow such as cavitation, flashing or condensation [55, 56]. Multiple studies in the past have investigated the various sources of vibrations in nuclear piping-equipment systems that can lead to subsequent leakage and failure [57, 58, 59, 60, 61, 62]. A few studies [63, 64, 65, 66, 67] have also proposed methodologies to model such piping vibrations and reduce the cumulative effect on the piping-equipment systems. Most of these studies are focused on flow-induced vibrations that occur due to vortex shedding, flow through valves or nozzles, etc. In nuclear facilities, pumps are required to facilitate numerous essential functions such as transporting coolant from reservoir to the reactor core. Numerous studies have been conducted in the past to characterize the vibrations and flow fluctuations that occur in piping systems due to the use of pumps such as centrifugal [68, 69, 70], reciprocating [71, 72, 73] and electromagnetic [74, 75, 76, 77]. Continuous vibrations over long periods of time can cause fatigue to build up at certain structural discontinuities of the
piping-equipment systems. Both high-cycle fatigue and low-cycle fatigue can cause sudden onset of cracks, leakages and breaks in the piping systems, which can eventually lead to a nuclear accident. The phenomenon of fatigue in nuclear piping-equipment systems due to cyclic loads, such as vibrations due to pump operations, has been detailed in past reports and related codes [78, 79, 80, 81]. Significant research has also been conducted on identifying and proposing retrofitting strategies for low-cycle fatigue [82, 83, 84, 85, 86]. However, capturing and preventing high-cycle fatigue that occurs due to pump-induced vibrations remains a challenging area in the design of piping-equipment systems [78]. This dissertation aims to enhance the proposed condition monitoring methodology such that can be applied towards preventing high-cycle fatigue in nuclear piping-equipment systems subjected to cyclic loads from pump-induced vibrations.

III.3 Problem Description

The equipment and connected piping safety systems of nuclear facilities experience normal operational vibrating loads caused by pump operations, flow-induced, or water hammer phenomenon. Part III focuses on the vibrations in piping-equipment systems due to pump operational loads. The decision to operate the pumps at a certain speed depends on the thermal hydraulic and power generation requirements of the NPP. Therefore, in the case of flow anomalies, different pumps connected to the piping systems can operate at different speeds. The speed of pump operations can determine the amount of vibrations and subsequent fatigue developed in the piping-equipment systems. Cyclic fatigue for prolonged duration of time can cause cracks and leakage in the piping safety systems.

Thus, as a supplementary guide to the current periodic maintenance and NDT procedures on nuclear piping-equipment systems, Part III proposes a condition monitoring framework which can capture and process real-time sensor data to detect degraded locations along with their severity. The condition monitoring framework is evaluated by using the Experimental Breeder Reactor (EBRII) nuclear reactor and its
corresponding data as an application case study [88, 89, 90, 124]. In this study, a part of the piping-equipment system from EBRII coolant system called ‘Z-pipe’ system shown in Figure III.1, is selected to develop a proof-of-concept for the proposed condition monitoring framework. The Z-pipe system is subjected to vibrational loads due to normal pump operations. An AI algorithm is developed and trained to detect degradation in this system. Stress concentrations at detected degraded sections of the Z-pipe system are determined and checked against the allowable ASME design criteria [79] to provide a scenario-based recommendation for safe pump operating speeds.

III.3.1 Vibrations in Piping-Equipment systems due to normal operations

In the nuclear industry, the equipment and connected piping systems can experience vibrations due to various sources [55, 56] such as:

- Mechanical induced sources: machinery unbalanced forces and moments, vibration of pumps.
Pressure pulsation induced sources: reciprocating compressor and pumps, turbine pulsations, centrifugal compressors and pumps

- Flow through pressure letdown, valves, orifice plates
- Flow turbulence
- Cavitation and flashing at pressure reducing valves, control valves, and flash tanks
- Vortex shedding
- Acoustical resonance
- Water and steam hammer

The above-mentioned sources can exhibit different modes of vibrations in the piping-equipment systems as tabulated in Table III.1. Over time and use, steady-state periodic and random vibrations can lead to material fatigue and subsequent failure at piping branch connections such as T-joints, threaded connections, elbows or nozzles.

Table III.1: Modes of Vibrations induced in equipment and piping systems

<table>
<thead>
<tr>
<th>Modes of Vibration</th>
<th>Cause of Vibration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Steady-State Periodic</td>
<td>Operating equipment such as reactor coolant pumps</td>
</tr>
<tr>
<td></td>
<td>Flow-induced due to pressure letdown, valves, orifice plates</td>
</tr>
<tr>
<td>Steady-State Random</td>
<td>Cavitation or flashing</td>
</tr>
<tr>
<td></td>
<td>Vortex shedding</td>
</tr>
<tr>
<td>Dynamic Transient</td>
<td>High/Low pressure pulse traveling through the fluid</td>
</tr>
<tr>
<td></td>
<td>Instant closure of the check valve(s), causing water hammer</td>
</tr>
<tr>
<td></td>
<td>External hazards such as earthquakes</td>
</tr>
</tbody>
</table>

In this research, steady-state vibrations due to pump operations are considered on the Z-pipe system. These steady-state vibrations can be harmonic (Figure III.2) with
a force amplitude and excitation frequency, as shown in Equation III.1.

\[ f(t) = F \sin(\omega_f t) \text{ or } F \cos(\omega_f t) \]  

(III.1)

where, \( f(t) \) is the harmonic excitation load, \( F \) is the force amplitude and \( \omega_f \) is the excitation frequency in radians/second. The discussion on obtaining the amplitude of force \( F \) is detailed in section III.5. The excitation frequency \( \omega_f \) varies with the speed of pump operations, as shown in Equation III.2 [64, 65].

\[ \omega_f = 2\pi \frac{nNP}{60} \]  

(III.2)

where, \( n \) is the frequency number, \( N \) is the number of blades/pump plungers/pistons in the pump being considered and \( P \) is the rotation speed of the pump.

![Figure III.2: Harmonic Excitation Load](image)

**III.3.2 EBRII Z Piping-Equipment System**

To develop the proposed condition monitoring methodology and demonstrate its capability for strategy-based recommendations on avoiding fatigue build-up, the ‘Z-pipe’ system is selected from EBRII nuclear reactor. The EBRII nuclear reactor is located at Idaho,
USA and was operational from 1964 until 1994. 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. This piping system is made up of schedule 10 pipe material and is composed of five straight pipe elements and four elbow elements with uniform thickness and flow area throughout the system. As shown in Figure III.3, a three-dimensional finite element model of the Z-pipe system is created and subjected to auxiliary pump-induced vibrations. As a part of this proof-of-concept condition monitoring framework, the auxiliary pump is assumed to operate between 620 rpm (rotations per minute) and 1000 rpm. Therefore, from Equation III.2, the excitation frequency range for pump-induced harmonic vibrations can be calculated as $62.8 - 106.8$ radians/second or $10 - 17$ Hz. A steady-state harmonic analysis is carried out by subjecting the Z-pipe system to 70 harmonic excitations between the range of excitation frequencies ($10 - 17$ Hz) with a 0.1 Hz frequency step and a unit amplitude of force. 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 III.3. The sensor response is collected in three orthogonal X, Y, and Z directions as an acceleration-time series signal, which is representative of triaxial accelerometer sensors installed on real SSCs.
III.3.3 Degradation and Uncertainty

Nuclear piping-equipment systems experience degradation in the form of pipe-wall thinning due to flow-assisted erosion and corrosion [6]. The loss of pipe-wall thickness can cause a subsequent reduction in structural stiffness of the system. Any change in the structural stiffness causes a variation in the dynamic characteristics and this is reflected in the acquired acceleration-time series sensor response. Similar to Part II of this dissertation, a reduction in the pipe wall thickness is characterized as the degradation in the piping-equipment system. Usually, the degradation occurs at certain hotspot locations in the system, such as the structural discontinuities at elbow, t-joint, nozzles, anchors, etc. [97, 98, 99, 100, 101, 102]. Therefore, for the Z-pipe system, degradation is instantiated at the two input and output nozzles, and the four bend-pipe elbows with two locations per elbow. This amounts to a total of ten potential degradation hotspot locations as illustrated in Figure III.4. For developing this framework, degradation is
assumed to occur at one location at any given instant of time. However, the amount of degradation severity at each location can vary depending on the amount of pipe-wall thinning observed.

Degradation Hot Spot Locations

![Degradation Hot Spot Locations in Z-pipe system](image)

Figure III.4: Degradation Hot Spot Locations in Z-pipe system

This research classifies degradation severity in three distinct levels of minor, moderate and severe, as a percentage loss of pipe-wall thickness due to erosion and corrosion phenomena. For example, a 10% degradation represents a 10% loss of pipe-wall thickness at a certain location of the system. Due to uncertainty in the amount of degradation severity at any given location, a uniform distribution with a lower bound and an upper bound is assumed for incorporating this uncertainty in the proposed condition monitoring framework. The three levels of degradation can be represented as [20%, 30%] for minor, [45%, 55%] for moderate, and [70%, 80%] for severe degradation. Within these ranges, random severity values are generated using a Latin hypercube simulation (LHS) and then utilized in the finite element model of the Z-pipe system for collecting simulated sensor response from the degraded state of the system.
III.4 Proposed Condition Monitoring Methodology

III.4.1 Signal Processing, Pattern Recognition and Feature Extraction

The condition monitoring framework is first implemented by converting the acquired acceleration-time series sensor response to its power spectral density (PSD) in the frequency domain (Figure III.5). In this study, PSD is used as a potential degradation-sensitive quantity of interest. The PSD of any signal represents the amount of power contained in the signal at various frequencies. For a time-series signal that is stationary in nature over a short time period and with $X(f)$ as its FFT, the PSD can be calculated as shown in Equation III.3.

$$PSD(f) = |X(f)|^2 \quad (III.3)$$

Two different degradation-sensitive feature extraction approaches are compared for their effectiveness in training the multilayer perceptron (MLP) ANN. With the first simplistic approach, only one degradation-sensitive quantity is extracted from each sensor’s response. The maximum value from the PSD curves, $PSD_{max}$, is extracted and saved in a database repository to be used as the training feature for detecting degradation in the
Z-pipe system. In the second approach, pattern recognition is implemented to extract the maximum difference observed between the non-degraded and degraded states of the Z-pipe system. This approach to extract a vector of four degradation-sensitive quantities has shown potential benefits in Part II of this dissertation over using a single degradation-sensitive quantity as the training feature for the AI algorithms. A representative vector for the sensor response shown in Figure III.5 has been tabulated in Table III.2.

Table III.2: Feature Extraction: Four Quantities of Interest

<table>
<thead>
<tr>
<th>QoIs</th>
<th>Definition</th>
<th>Sample Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$PSD_{max}$</td>
<td>Maximum PSD amplitude from degraded response</td>
<td>199.42</td>
</tr>
<tr>
<td>$\Delta_{max}PSD$</td>
<td>Maximum difference observed in significant PSD peaks</td>
<td>6.55%</td>
</tr>
<tr>
<td>$\omega_{\Delta}$</td>
<td>Frequency corresponding to $\Delta PSD_{max}$</td>
<td>13.57 Hz</td>
</tr>
<tr>
<td>$PSD_{0,\Delta}$</td>
<td>non-degraded PSD peak corresponding to $\Delta PSD_{max}$</td>
<td>161.08</td>
</tr>
</tbody>
</table>

III.4.2 Deep Learning approach with ANNs

The equipment and connected piping systems at nuclear facilities can generate large amounts of sensor data, making data interpretation the biggest challenge for a condition monitoring framework. The use of deep learning algorithms such as the MLP ANN is proposed for data handling and processing. Thus, eliminating the need to correlate different degradation-sensitive quantities and formulate degradation indices based on structural behavior assumptions, as explained in Part II of this dissertation. Raw sensor data can be processed and fed into the deep learning algorithms to predict degraded locations and assess the structural life of nuclear piping-equipment systems.

The design and architecture of an MLP ANN can affect its performance for condition monitoring applications. Hence, Part II of this dissertation focuses on
developing a generic design of the deep learning algorithm that can be applicable to most nuclear piping-equipment systems. This part of the dissertation focuses on applying the previously proposed deep learning algorithm to piping-equipment systems subjected to vibrational operating loads. The key parameters of the proposed MLP ANN are tabulated in Table III.3.

Although this study and Part II of this research aim at designing a generic architecture of the ANN for detecting degradation in various nuclear piping-equipment systems, some parameters such as the number of input neurons and number of output neurons will be subject to change depending on factors as elaborated below:

Table III.3: ANN Training Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of hidden layers</td>
<td>3</td>
</tr>
<tr>
<td>Optimizer</td>
<td>Adam</td>
</tr>
<tr>
<td>Epochs</td>
<td>2000 with early stopping criteria</td>
</tr>
<tr>
<td>Learning Rate</td>
<td>0.001</td>
</tr>
<tr>
<td>Batch Size</td>
<td>16</td>
</tr>
<tr>
<td>Dropout</td>
<td>0.5</td>
</tr>
<tr>
<td>Activation Functions</td>
<td>PReLu and softmax</td>
</tr>
<tr>
<td>Validation split</td>
<td>30%</td>
</tr>
</tbody>
</table>

- **Input neurons:** The number of input neurons is governed by the number of sensors selected for training and testing the deep learning algorithm. It also depends on the type of sensor being used i.e. uniaxial, biaxial or triaxial sensors. In this study, 12 triaxial sensors are assumed to be installed on the Z-pipe system. Therefore, the input layer of the ANN will be made up of $12 \times 3 = 36$ neurons. A sensor placement
strategy, as proposed in Part II of this dissertation, is also investigated as a part of the condition monitoring framework for the Z-pipe system. Instead of 12 sensors, only 8 sensors, as illustrated in Figure III.6 are considered at the four elbows of the Z-pipe system and the results for both the sensor placement formulations are compared. For the scenario with 8 triaxial sensors, the ANN will contain \(8 \times 3 = 24\) input neurons.

![Figure III.6: Z-pipe Reduced Sensor Placement Strategy](image)

- **Output neurons**: The number of output neurons is governed by the number of classes the ANN is expected to predict at the end of the training and testing phase. In the proposed condition monitoring framework, the number of classes is dependent on the number of potential degradation hot-spot locations on the system as well as the number of degradation severity levels being considered. For the Z-pipe system, 10 potentially degraded locations are investigated along with 3 degradation severities of minor, moderate and severe at each such degraded location. Therefore, the ANN can have only 10 output neurons if the desired output is predicting only the degraded locations. However, if the nuclear operators require information on the degraded
locations as well as their corresponding severity levels, the ANN architecture should incorporate a total of $10 \times 3 = 30$ output neurons.

The design of the selected MLP ANN with three hidden layers is illustrated in Figure III.7, where $n_i$ represents the number of input neurons and $n_o$ represents the number of output neurons.

![Figure III.7: MLP ANN Architecture]

Figure III.7: MLP ANN Architecture
III.4.3  Accuracy of Proposed Condition Monitoring Framework

Next, the proposed condition monitoring methodology is implemented on the Z-pipe system to detect degraded locations as well as the corresponding degradation severity levels. Table III.4 illustrates the results obtained from testing the proposed framework for the various aforementioned feature extraction techniques, sensor placement formulations and MLP ANN architectures.

Table III.4: Accuracy of Proposed Condition Monitoring Framework

<table>
<thead>
<tr>
<th>Model</th>
<th>Predict Locations</th>
<th>Predict Locations and Severity</th>
</tr>
</thead>
<tbody>
<tr>
<td>12 Sensors</td>
<td>86%</td>
<td>74%</td>
</tr>
<tr>
<td>1 QoI: $PSD_{max}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12 Sensors</td>
<td>99%</td>
<td>97%</td>
</tr>
<tr>
<td>Vector of 4 QoIs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8 Sensors</td>
<td>98%</td>
<td>97%</td>
</tr>
<tr>
<td>Vector of 4 QoIs</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*QoI: Quantity of interest

It is observed that using a vector of four degradation-sensitive quantities yields much higher prediction accuracy when compared to using only one degradation-sensitive quantity of $PSD_{max}$. Therefore, the deep learning algorithm is able to extract and learn much more beneficial information from the proposed pattern recognition and feature extraction technique than from previous methodologies built for structures such as buildings, bridges, etc. This is true especially for predicting the degradation severity in addition to the degraded locations where using only one quantity of interest resulted in a 86% prediction accuracy whereas using the vector increased the prediction accuracy to 97%. For the sensor placement formulations, using 12 sensors yielded almost similar
results than using only 8 at elbow locations of the system. The proposed framework utilizing sensor data from only 8 sensors is able to predict degraded locations as well as the degradation severity levels with 97% accuracy. This is considerable jump from the 74% accuracy obtained by using $PSD_{max}$ as the only degradation-sensitive quantity. These results provide confidence in the proposed sensor placement formulation as well as the richness of degradation-sensitive data contained in the extracted vector.

In Part III, the results predicted by the proposed monitoring methodology are studied even further by conducting a thorough investigation into the cases that are predicted erroneously for degraded locations as well as the severity levels. The methodology is able to achieve an accuracy of 97% when considering data from 12 sensors as well as from only 8 sensors. Figure III.8 illustrates the actual output classification versus the predicted output classification using both the sensor placement strategies.

![Figure III.8: Actual versus Predicted Classifications](image)

The number of erroneous predictions are further investigated to obtain cases in which the proposed methodology is able to predict:

- Case 1: the correct degraded location with a wrong degradation severity level.
• Case 2: an adjacent degraded location which is very close to the actual degraded location or the second location from the same elbow joint.

• Case 3: a degraded location which is not adjacent to the actual degraded location.

The total number of erroneous predictions for these three cases are tabulated in Table III.5. For Case 1 predictions, current NDT techniques can be applied at these accurately predicted degraded locations to confirm the actual degradation severity level. For predictions designated as Case 2, it can be recommended that for any degraded location predicted by the proposed monitoring framework, the current NDT techniques should also be applied to other adjacent potential hot spots on the piping system as an extra safety measure.

Table III.5: Analysis of the Predicted Results

<table>
<thead>
<tr>
<th>No. of Sensors</th>
<th>Correct Predictions</th>
<th>Erroneous Predictions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Case 1</td>
</tr>
<tr>
<td>12</td>
<td>610</td>
<td>6</td>
</tr>
<tr>
<td>8</td>
<td>614</td>
<td>3</td>
</tr>
</tbody>
</table>

It is shown that out of a total of 630 testing scenarios, very few scenarios fall into the category of Case 3 in which the predicted locations are far-off from the actual degraded areas. These Case 3 scenarios make up for approximately 2% of the total cases the condition monitoring framework with 8 sensors is being tested for. Therefore, approximately 98% of the total test cases can be caught early on for degradation detection by implementing the proposed methodology and reduced sensor placement strategy. Part IV of this dissertation explores various other signal processing and deep learning algorithms such as convolutional neural networks for better performance.
III.5 Strategy Based Assessment for Avoiding Fatigue

III.5.1 Fatigue and ASME Design Criteria

Piping-equipment systems under repetitive or cyclic forms of loading can experience failure due to fatigue, such as formation and propagation of cracks and leakages. Fatigue failures can occur due to cyclic loads at significantly lower stresses than the yield stress of the material. At lower than yield stress values, cyclic loading can cause microscopic cracks which over time and use can grow into macroscopic cracks. These macroscopic cracks can result in structural failure of the material and component. The microscopic cracks typically initiate at locations with structural discontinuities in the system such as nozzles, elbows, t-joints, etc. for nuclear piping-equipment systems. Any defective welding in such systems can also be a potential fatigue build-up hot spot location. Degradation in nuclear piping systems due to flow-assisted corrosion and erosion can result in quicker transformation of a microscopic crack to a macroscopic structural defect. Thus, a condition monitoring framework utilizing sensor data from the systems can act as an additional safety tool, by detecting potential degraded locations well in advance of fatigue build-up and cracks.

The damage caused due to fatigue can be classified in two broad categories of high-cycle fatigue and low-cycle fatigue. High-cycle fatigue is usually observed in the elastic regions of material behavior whereas low-cycle fatigue is characterized by plastic behavior of materials. Vibrations in nuclear piping systems, caused due to pump operations or thermal cycles, are characterized as high-cycle fatigue where the amplitude of stress or excitation force is small and the number of cycles to reach fatigue failure are large. As per the ASME operation and maintenance (O&M) [81] design criteria for safety against fatigue failures, either the stresses developed in the piping system should be monitored to be well below the material’s yield stress limits, or the cause of high-cycle vibrations must be eliminated or reduced. This study proposes a novel approach that enhances
the condition monitoring framework by providing recommendations on eliminating or reducing the cause of high-cycle fatigue by pump-induced vibrations. On the other hand, low-cycle fatigue is caused by large amplitudes of sudden force, such as water-hammer, and it requires low number of cycles to achieve fatigue. Typically, unlike high-cycle fatigue, existing methodologies can define, analyze and account for low-cycle fatigue in the design phase of the piping components [82, 83, 84, 85, 86].

Steady-state vibrations with low amplitudes in nuclear piping-equipment systems can cause high cycle fatigue. Over time, this can cause fatigue-induced cracking at discontinuities in the piping components. Two aspects are required for the analysis of any piping-equipment components subjected to fatigue. The first aspect relates to calculation of the cyclic load that would cause high-cycle fatigue. In this study, the pump-induced vibrations during normal operations are considered to cause high-cycle fatigue to the nuclear piping-equipment system. The second aspect deals with predicting potential degraded locations and obtaining the maximum stresses developed in these regions of the piping components. This can be achieved by implementing the proposed condition monitoring framework and augmenting it to obtain the stresses generated, as detailed in the following subsections. Then, the stresses experienced by the piping-equipment system can be checked against the allowable stresses and the number of cycles to fatigue as defined by the S-N curves illustrated in (Figure III.9). These S-N curves are provided in the ASME BPVC II [79].
In ASME III NB-3121 design code [80], which provides guidelines on fatigue design for nuclear SSCs subjected to cyclic loads, it is stated that, “the tests on which the design fatigue curves (Figs. I-9.0) are based did not include tests in the presence of corrosive environments which might accelerate fatigue failure”. This study proposes a cutting-edge technique to combine the condition monitoring framework with fatigue-life assessment for nuclear piping-equipment systems, by providing a strategy-based recommendation on “safe” pump operating speeds.

### III.5.2 Pump Induced Vibrations

The piping-equipment systems can be subjected to various sources of vibrations, as detailed in section IV.2, this study focuses on the vibrations caused due to pump operations. The use of pumps such as reciprocating, centrifugal, electromagnetic, etc. can cause vibrations due to pressure pulsations in the fluid flow, vortex phenomenon, or mechanical
movement of the pump machinery. In the past, some studies have focused on developing models that demonstrate the vibration characteristics of pump operations, such as the frequency of excitation, amplitude of the excitation force and the phase of excitation [57, 58, 59, 60, 61, 62].

Pumps can lead to pressure pulsations through the fluid being transported due to the normal operating mechanics of the pump. For reciprocating pumps, the mechanical action of the piston rod causes these pressure pulsations, whereas in centrifugal pumps, the rotating blades can cause changes in fluid pressure as well as vortex shedding phenomenon. In electromagnetic pumps, pressure pulsations can occur due to the rotation of the liquid metal fluid by the magnetic force field generated by the pump [74, 75, 76, 77]. In the application case study with EBRII Z-pipe system, the auxiliary pump is a direct current electromagnetic conduction reactor coolant pump. Another pump attached to the primary piping system for EBRII, called the primary sodium pump, is centrifugal in nature. The pressure pulsation in the fluid can be characterized for a DC electromagnetic pump [74] and a centrifugal pump [69] using Equation III.4 and Equation III.5, respectively.

\[
P(\text{pressure}) = \frac{I(\text{current}) \times B(\text{magnetic field})}{s(\text{height of flow channel})} \quad \text{(III.4)}
\]

\[
p_d = \frac{1}{2} \left( e^{j \frac{\pi}{2} \sqrt{1-j \xi l}} + e^{-j \frac{\pi}{2} \sqrt{1-j \xi l}} \right) p_s - \frac{c \sqrt{1-j \xi l}}{A} \frac{1}{2} \left( e^{j \frac{\pi}{2} \sqrt{1-j \xi l}} - e^{-j \frac{\pi}{2} \sqrt{1-j \xi l}} \right) m_s \quad \text{(III.5)}
\]

where \(p_d\) is the pressure at the discharge of the pump, \(c\) is speed of sound, \(\omega\) is the angular velocity, \(\sigma\) is pipe resistance, \(l\) is length of equivalent pipe element, \(p_s\) is the pressure at the suction of the pump, \(m_s\) is the mass flow at the suction of the pump, and \(A\) is the cross-sectional area of the pipe.

The pressure exerted by the fluid on the EBRII Z pipe system can be attributed to various sources including, but not limited to, pressure pulsations due to auxiliary...
pump operations and flow-induced vibrations, pressure of the fluid flowing through the piping system, etc. An accurate measurement of the induced pressure can be captured by installing pressure sensors that detect the exact pressure pulse signals from the fluid flowing through the piping system. However, since this study primarily focuses on capturing sensor data from accelerometer sensors installed on piping-equipment systems, such acceleration-time series signals are generated by conducting high-fidelity simulations of the Z-pipe subjected to harmonic excitations due to the auxiliary pump-induced vibrations. The preliminary nature of any harmonic excitation force $f(t)$ and the amplitude of the excitation force, $F$, at any location of the piping-equipment system, can be calculated as shown in Equation III.6.

$$f(t) = F \sin(\omega_f t) \text{ or } F \cos(\omega_f t)$$

$$F = p \times A$$

(III.6)

where $p$ is the pressure exerted by the fluid on the piping element and $A$ is the area of cross-section of the piping element. The frequency of excitation $\omega_f$ can be calculated from the pump operating speed as given by Equation III.2.

The EBRII Z-pipe system being considered as the case study in this research has a uniform cross-section of flow area, $A$, equal to 240.5 in$^2$ throughout its entire length, with a pipe outer diameter of 18 in and pipe wall thickness of 0.25 in. The next step involves calculating the value of pressure $p$ exerted on the Z pipe system due to the vibrations emitting from auxiliary pump operations. One option would be to utilize the pressure pulsation equation for electromagnetic pumps, as illustrated in Equation III.4. In this study, the concept of calculating pressure pulsations is not explored further due to lack of data on the auxiliary pump specifications. Another approach to calculate the value of pressure $p$ could be to acquire the maximum design pressure of the fluid flowing through the Z pipe system. From previous documentation on EBRII operations [89, 90, 124], this
pressure is obtained as 6.51 psi for the Z-pipe system with liquid sodium at 900°F. By substituting this value in Equation III.6, the maximum amplitude of harmonic excitation force can be calculated as shown in Equation III.7.

\[ F = p \times A = 6.51 \times 240.5 = 1565.65 \text{ lbs} \]  \hspace{1cm} (III.7)

The methodology presented in this research takes on a simplistic approach by assuming the value of pressure \( p \) to be equal to \( \frac{1}{A} \), so that the amplitude of harmonic force excitation \( F \) is obtained as unity for conducting high-fidelity simulations of the Z-pipe system with harmonic excitation loads. This can be justified because the amplitude of excitation force is directly proportional to the pressure exerted by the fluid on the piping-equipment system. Thus, the sensor response acquired by subjecting the Z pipe system to a unit amplitude of harmonic excitation force can be scaled proportionally to accommodate for actual values of pressure \( p \), if available from EBRII documentation [89, 90, 124]. For the proposed condition monitoring framework utilizing AI techniques, this linear scalability is found to offer no advantages or disadvantages, as the AI algorithm compares various degradation-sensitive features which are extracted using the same scale of excitation force amplitude. Therefore, calculating the actual excitation force value due to pump-induced vibrations on the Z pipe system has been out of the scope of this research.

### III.5.3 Application Example Case Study

The primary goal of this part of the research is to open a new pathway for integrating the fatigue-life of piping-equipment systems subjected to vibrations during normal operations and the proposed condition monitoring framework. The EBRII Z-pipe system is used in concordance with the proposed condition monitoring framework to build an application example case study for the strategy based assessment with recommendations for “safe” pump speeds. As shown in Figure III.1, the auxiliary pump is attached to the Z-pipe
system. Therefore, it can be assumed that the Z-pipe system will be subjected to vibrations due to normal auxiliary pump operations. An example flowchart of the strategy based assessment is shown in Figure III.10 and each step of the flowchart is detailed in the following discussion.

**Diagnosis of Piping-Equipment System:**
Predict Degraded Location and Severity

Transmissibility Ratio plot

Calculate Bending Stresses within high Transmissibility Ratio range

Obtain Maximum Bending Stress and corresponding Pump Operating Speed

ASME Design Criteria: S-N Curves

Compare the Stress Values

Provide Recommendations on “safe” Pump Operating Speeds or, Allowable Number of Cycles

Figure III.10: Strategy Based Assessment Flowchart

1. **Diagnosis of Piping-Equipment System:** For the first part of the strategy based assessment, the proposed condition monitoring framework is utilized to detect any degraded locations on the Z-pipe system along with its degradation severity. This information is provided to the maintenance operators as well as saved into the
condition monitoring database for further investigation. In this hypothetical example, it is considered that the condition monitoring framework predicts minor degradation at Nozzle 1 of the Z-pipe system.

2. *Transmissibility Ratio Plot*: Next, the transmissibility ratio plot is generated for the degraded location subjected to various auxiliary pump operating speeds and corresponding frequencies of excitation. Transmissibility means amplification of the system’s response. Typically, the largest amplifications are observed when the natural frequency of the piping-equipment system resonates with the frequency of excitation from pump operations. If $\ddot{u}$ is the maximum acceleration obtained from the sensor response at the degraded location, and $\ddot{u}_0$ is the maximum acceleration from the harmonic excitation imparted by pump operations, then the transmissibility ratio can be obtained as shown in Equation III.8.

\[
\text{Transmissibility Ratio} = \frac{\ddot{u}}{\ddot{u}_0}
\]  

(III.8)

The sample transmissibility ratio plot for minor degradation at Nozzle 1 of the Z-pipe system is illustrated in Figure III.11.
transmissibility ratio values are selected. In this example, all the frequencies of excitation for which the transmissibility ratio value is more than 30 are selected, as highlighted in Figure III.11. A corresponding excitation frequency range of approximately $13 - 15\text{Hz}$ is obtained.

3. **Calculate Bending Stresses**: Using high fidelity simulations, the bending stresses generated at the diagnosed degraded location are extracted for the excitation frequency range with the highest transmissibility ratio values. Figure III.12 illustrates the bending stresses at Nozzle 1 of the Z-pipe system for the selected excitation frequency range.

![Figure III.12: Bending Stress Plot](image)

4. **Obtain Maximum Bending Stress and the Corresponding Pump Operation Speed**: The next step involves capturing the maximum bending stress experienced at the degraded location as well as the corresponding frequency of excitation due to pump operations. From Figure III.12, the maximum bending stress at Nozzle 1 of the Z-pipe system is found to be 22 psi at $14.7\text{ Hz}$ of excitation frequency. This excitation frequency is equivalent to an auxiliary pump operating speed of 882 RPM from
5. *ASME Design Criteria for Allowable Stress Values:* The ASME BPVC II [79] provides stress vs. number of cycles curve (S-N curve) which detail the allowable stress values for various materials of boiler and pressure vessels (including the connecting piping systems) versus the number of fatigue cycles before fatigue can cause cracks and leakages in the system. In this example, the Z-pipe system is made up of Type 304 stainless steel schedule 40 pipe. The corresponding ASME S-N Curve for austenitic steels is shown in Figure III.9 where the y-axis represents the allowable stress value in ksi, and the x-axis represents the number of cycles, \( N \), before fatigue can cause failure in the system.

For lower allowable stress values, a high number of cycles can cause fatigue failure, whereas for higher stress values, a low number of cycles can cause fatigue failure. This logarithmic SN Curve provides guidelines for allowable stress values at or above 13.6 ksi. However, in the example being considered, the maximum bending stress from Nozzle 1 of Z-pipe system is obtained as 22 psi. The value of bending stress is proportional to the amplitude of force experienced at the piping-equipment system from the pump-induced vibrations. In this research, a unit amplitude of force is assumed due to the auxiliary pump vibrations. However, based on previous discussion in subsection III.5.2 about the phenomenon of pressure pulsations due to pump operations and the maximum pressure exerted by the fluid flowing through the pipe system, it appears that the amplitude of excitation force would be much higher than unity for operating pumps and piping-equipment systems. Since the primary focus of this study is to develop a proof-of-concept condition monitoring framework and a strategy assessment based on sensor data collected from high-fidelity simulations, the calculation of actual excitation force from pump operations is not explored further as an objective of this research. In this hypothetical example, it can be shown that if the amplitude
of excitation force is $10^3$ lbs, then the maximum bending stress experienced at Nozzle 1 of the Z-pipe system will increase proportionately to 22 ksi from previously acquired 22 psi. Assuming this hypothesis, a maximum number of $3 \times 10^5$ cycles can be obtained for 22 ksi allowable stress value from the ASME S-N Curve illustrated in Figure III.9.

6. Provide Strategy-Based Assessment on Pump Operating Speeds: The last step is to provide a potential recommendation on pump operating speeds that would tend to avoid fatigue at hot spot degraded locations of the piping-equipment system. This recommendation will be composed of two aspects. One aspect relates to avoid a certain pump speed in RPM during normal operations. However, due to the thermal hydraulic and power generation needs of a nuclear reactor, it is not always possible to avoid a certain pump operating speed. Therefore, the second aspect of the proposed recommendation would detail the total number of hours the pump can be allowed to operate at that speed, as permitted by ASME design criteria for fatigue. For the example being considered, since the maximum bending stress at Nozzle 1 is developed at a pump speed of 882 RPM, the first potential recommendation to the operator will be to avoid operating the pump at 882 RPM. For the second potential recommendation, the allowable number of hours to operate the pump at 882 RPM can be calculated as 5.6 hours from Equation III.9.

$$\text{Allowable hours, } h = \frac{N}{\text{Pump speed in RPM} \times 60}$$

$$\implies h = \frac{3 \times 10^5}{882 \times 60} = 5.6 \text{ hours} \quad (\text{III.9})$$

where, $N$ is the number of cycles from SN curve.

Thus, with a hypothetical example, it is shown that the proposed condition monitoring framework can be extended in its applicability by providing potential recommendations to the operator regarding pump speeds that can cause excessive
fatigue at hot spot degraded locations in the piping-equipment systems.

III.6 Summary and Conclusions

Critical vibrations caused by pressure pulsations in the fluid due to pump operations can cause cracks and leakages in nuclear piping systems. Generally, these vibrations result in high-cyclic fatigue failure which is difficult to detect with current NDT techniques and scanning processes prevalent in the nuclear industry. This study is aimed at developing an AI based condition monitoring framework that can detect degraded locations along with their degradation severity level for a nuclear piping-equipment system. For the case study, the Z-pipe system from EBRII nuclear reactor is considered and subjected to the auxiliary pump-induced vibrations. The acquired sensor response is converted to an acceleration-time series signal, and then the PSD is extracted as the degradation-sensitive tool. It is observed that the proposed condition monitoring framework is able to detect degraded locations and their severity with 97% accuracy for the Z-pipe system. The proposed methodology is also extended to include a strategy based assessment on the pump operating speeds in order to avoid fatigue build-up due to pump-induced vibrations. The key conclusions of the study are summarized as follows:

- The pattern recognition and feature extraction technique proposed in Part II of this dissertation is applied to a piping-equipment system subjected to vibrations due to normal pump operations. In Part II, the proposed methodology demonstrates good results for a piping system subjected to a post hazard scenario, with the power spectral density containing multiple unique peaks. In contrast, the power spectrum, obtained from the sensor response of a piping system subjected to normal operating loads, is observed to be smooth with fewer peaks. In spite of this characteristic difference in the captured power spectral density, the proposed condition monitoring methodology is able to extract well-defined degradation-sensitive features.

- It is shown that using a vector of degradation-sensitive quantities is better than
using a single degradation-sensitive quantity, since the vector can capture essential features from all modes of vibration in piping systems. A loss of response from lower order modes of vibration can occur if a single quantity is used for creating the ANN training database.

- A deep learning algorithm using an MLP ANN is designed along with a sensor placement strategy for predicting degraded locations in the EBRII nuclear reactor’s Z-pipe system. Using this algorithm and a reduced sensor placement strategy, the condition monitoring methodology is able to detect degradation due to flow-assisted erosion and corrosion with 98% accuracy.

- The importance of detecting degradation severity level along with the degraded location is demonstrated since different locations can experience varying intensities of degradation severity. The proposed methodology achieved a 97% accuracy in predicting the degraded locations and classifying the corresponding level of severity as minor, moderate and major. Uncertainty in these classifications levels is also considered by assuming a uniform distribution with a lower and upper bound for each of the levels.

- An in-depth analysis of the erroneous predictions is carried out to gain an insight into the performance of the deep learning network. It is found that about only 2% of the total test cases predicted locations that were far from the actual location experiencing degradation.

- An enhancement to the proposed condition monitoring framework is demonstrated by including a strategy based assessment to avoid high-cyclic fatigue at hot spot degraded locations of the piping system. An application example is presented for the Z-pipe system which compares stresses at degraded locations to the ASME design criteria for fatigue. Two potential recommendations are specified on safe pump operational speeds as well as the allowable number of cycles or hours the pump can be operated at certain speeds, before fatigue can cause cracking and leakage failure.
in the piping system.
PART IV

A Comparative Study on Deep Learning Approaches for Condition Monitoring of Advanced Reactor Piping Systems
IV.1 Introduction

With advances in deep learning algorithms and artificial intelligence, autonomy in advanced nuclear reactors by utilizing the Digital Twin (DT) concept [87, 88, 117, 125, 126, 127, 128] looks achievable. In reactor autonomy, there are various degrees of automation ranging from providing action alternatives to deciding and acting independently without an operator. Choosing a level of autonomy depends on the trade off between staffing, operational flexibility, system flexibility, and safety. A highly autonomous system should demonstrate reliability with little human assistance and be able to process all operating modes by planning actions based on sensor data and identifying the subsequent consequences of its actions. Advanced nuclear reactors have the potential to provide factory-fabricated, safe, and transportable nuclear energy to civilian, industrial, and defense industries. In concept, advanced nuclear reactors are similar to traditional reactors, however, they can be smaller in size, simpler in design and exhibit higher efficiency.

Although various types of advanced reactors can be designed, such as small modular reactors, molten salt reactors, sodium-cooled reactors, gas-cooled reactors, water-cooled reactors, etc. [129], one common aspect across all these reactors remains the use of coolants to extract residual heat from the nuclear fission reaction taking place in the reactor core. Piping-equipment systems are required to transport coolant effectively from one vessel to another at a nuclear facility. Any loss of coolant due to degradation and damage in such piping-equipment systems can lead to a nuclear accident. Hence, it is important to identify any degradation in nuclear piping-equipment systems. With the promise of autonomous control in advanced reactor systems [115, 116, 118, 119, 120, 121, 122], a condition monitoring framework that can detect even minor degradation in nuclear piping systems can prove to be advantageous. Part II and Part III of this dissertation are aimed at designing such a condition monitoring framework by utilizing AI techniques.
for nuclear piping-equipment systems. Part IV explores the relative computational and predictive capability of various deep learning algorithms such as multilayer perceptron (MLP) artificial neural networks (ANNs), one-dimensional convolutional neural networks (1-D CNNs) and two-dimensional convolutional neural networks (2-D CNNs) within the proposed data-driven condition monitoring design.

Structural health monitoring (SHM) or condition monitoring is an important component of an autonomous control system or digital twin developed for any nuclear power plant (NPP) [7, 8]. Traditionally, many SHM methodologies have been developed for detecting damage such as cracks and fissures in structural systems [23, 24, 25, 26, 27, 130, 131, 132, 133, 134, 135]. In recent years, most SHM studies have been focused on detecting anomalies in the systems by utilizing powerful machine learning algorithms such as supervised as well as unsupervised learning techniques [20, 21, 22, 91, 92, 93, 95, 96, 136]. It has been found that for applications where previously collected sensor data can accurately represent a degraded state of the system, supervised learning techniques such as deep learning with neural networks can provide astonishing results in detecting damages [1, 2, 3, 4, 43, 44]. However, these methodologies have been developed primarily for buildings, bridges and buried utility pipeline networks. In comparison to these applications, the sensor data collected from nuclear piping-equipment systems can demonstrate different dynamic behavior, as detailed in Part II and Part III of this dissertation. Furthermore, previous studies concentrate on detecting cracks and fissures which are illustrative of significant damage in nuclear piping systems. Therefore, a condition monitoring framework built for piping safety systems in nuclear facilities, should be capable of detecting even minute changes in the acquired sensor data and capture various levels of degradation such as minor, moderate or severe.

From past studies [3, 4, 45, 46, 47, 48, 49, 50, 51, 52, 53, 94] it seems like CNNs can be beneficial in capturing some of the highest level of degradation-sensitive features
from sensor response acceleration-time series data. The primary advantage of using CNNs is that they can automatically extract required features from the input data, without requiring significant data pre-processing. This has been demonstrated in a few studies [3, 4] where the CNNs are trained on the acceleration-time-series signals. CNNs were initially invented for image recognition using 2D image data. Hence, at their heart, CNNs perform the best for classification of images and computer vision applications. Therefore, CNNs can be trained on the images of acquired acceleration-time series signals to detect structural anomalies in a long-span bridges [45]. In a similar study [46], images from accelerometer sensor data are used for data augmentation and to detect damage in steel jacket-type wind turbine foundations using CNNs. Some studies [47, 48, 49] have explored CNNs for detecting cracks or holes in plate structures. Guided wave imaging, electromagnetic impedance signatures or ultrasonic signals are used to train the CNNs. Another study [50] investigates the role of transmissibility functions and 1D CNNs in detecting damage for a building frame structure along with consideration of white noise in the sensor data. CNNs are also used to create pretrained networks such as Alexnet and ResNet. Some papers [51, 52, 53] utilize the power of such pretrained networks with transfer learning approaches and images obtained from the structural systems (such as cable stayed bridges, towers, concrete structures) to detect damages or for signal denoising.

Although all the above-mentioned studies proposed powerful SHM methodologies to detect damages using CNNs, most of them concentrate on using the entire acceleration-time series signals for 1-D CNNs or on image recognition using 2-D CNNs. However, for piping systems in nuclear power plants (NPPs), enormous sensor data can be generated and it can be difficult to process the complete signals obtained from accelerometer sensors without requiring high computational resources. Therefore, this research explored alternate data preprocessing techniques to detect degradation with minimum computational complexity. Furthermore, it is not always possible to get image data for every location on the piping system that can potentially degrade with time.
Therefore, this study also investigates the use of Short-Time Fourier transform (STFT) technique to develop 2-D input data for 2-D CNNs [54].

A data-driven condition monitoring framework built for nuclear piping-equipment systems can prove to be an advantageous component for any autonomous advanced nuclear reactor control system. Thus, this research aims at exploring the performance of various deep learning algorithms such as MLP ANNs and CNNs in detecting degradation locations and their degradation severities for nuclear piping safety systems subjected to a post-hazard scenario as well as vibrations occurring due to normal pump operations at the nuclear reactor. The sensor data collected from high fidelity simulations is transformed from its time-domain to its frequency domain to obtain the PSD and to its time-frequency domain to acquire the STFT. Both the signal processing approaches are compared for their relative degradation-diagnostic capability. One challenge of applying deep learning algorithms to inverse problems is the concept of overfitting the training data. This research explores numerous techniques such as regularization, dropout, early stopping, validation, etc., to avoid overfitting in the network’s performance. The computational resources required for implementing the deep learning algorithms are also compared. While a post-hazard scenario can necessitate the use of a deep learning algorithm with the quickest prediction on the degraded state of piping safety systems, a real-time condition monitoring framework during normal operations can allow for more accurate and computationally expensive AI methodologies.

IV.2 Problem Description

The operational functionality of advanced nuclear reactors can be governed by the integrity of its various structures, systems and components. One such component is the piping-equipment system which interconnects numerous equipment like the reactor core, pumps, steam generators, etc. As a part of any autonomous control system of advanced nuclear reactors, a robust condition monitoring framework to detect degradation in these piping-
equipment systems can be beneficial. Sensor data collected from the piping-equipment system can be processed to extract information about the system’s current degraded state. This can result in an increased level of monitoring, control, supervision, and security by allowing the operators to obtain knowledge about the degradation severity at various locations of a piping safety system instead of relying on a predetermined maintenance schedule.

In this study, three different deep learning algorithms such as MLP ANN, 1-D CNN and 2-D CNN, are designed and utilized for the proposed condition monitoring framework. Two signal processing and feature extraction methodologies (1-D PSD and 2-D STFT) are also implemented to compare the relative diagnostic capabilities. To avoid any overfitting of the model, validation and regularization is also carried out on the deep learning models. These methodologies are designed using a simple piping system as the application case study, and are further implemented, for illustrating the effectiveness, on a Z-pipe system from EBRII nuclear power plant. The simple piping system is subjected to a collection of earthquake loads whereas the Z-pipe system from EBRII is subjected to pump-induced vibrations during normal operations. Computational resources required for each of these methodologies as well as the output prediction accuracies are compared to assess the performance of the proposed networks.

IV.3 Simulation Models of Nuclear Piping-Equipment Systems

IV.3.1 Case Study 1: Simple Piping System

A simplistic three-dimensional piping-equipment system, similar to a USNRC piping benchmark problem [103], is selected for designing and testing various deep learning and signal processing algorithms within the condition monitoring framework. The finite element (FE) model of the system, illustrated in Figure IV.1, is created and described in Part II of this dissertation. It consists of two elbows, three straight sections of pipe and a
vertical hanger. The acceleration-time series sensor data is collected from all nine sensor locations on the system. Part II of this dissertation details an exploratory study on the reduced sensor placement strategy. This reduced sensor strategy is also used to generate and compare results in section IV.6. Each sensor is assumed to collect acceleration-time series data in three orthogonal directions of X, Y and Z. The piping system is subjected to a collection of 100 earthquake records in order to generate high fidelity sensor data.

Degradation in the system is assumed at four elbow locations and one nozzle. The FE model is updated to represent degradation due to flow assisted erosion and corrosion, at each of these locations, one at a time, by reducing the thickness of the pipe wall elements. As detailed in Part II of this research, degradation is classified as minor, moderate or severe, depending on the percentage of pipe wall thickness reduction. Uncertainty in degradation severity is quantified as a uniform distribution with a lower and upper bound for each classification level i.e., [20%, 30%] for minor, [45%, 55%] for moderate, and [70%, 80%] for severe degradation. Latin hypercube sampling is utilized...
to obtain random degradation severity values for the FE simulations and sensor data collection.

IV.3.2 Case Study 2: Z-Pipe System from EBRII

For the second case study, the Z pipe system from EBRII nuclear reactor is considered. An electromagnetic auxiliary pump is attached to the Z pipe system, as illustrated in Figure IV.2. Therefore, it is assumed that the Z pipe system will experience harmonic vibrations due to the auxiliary pump’s normal operations as shown in Figure IV.3. The phenomenon of pump-induced vibrations is detailed in Part III of this dissertation.

![Figure IV.2: EBRII Primary Tank Layout including the Z-pipe system [124]](image-url)
Discontinuities in the Z pipe system, such as the four elbows and two nozzles, are selected as the potential degraded locations. The system is subjected to 70 frequencies of harmonic excitation ranging from $10^{-17}$ Hz in order to generate sensor data from FE simulations. Two different sensor placement strategies are considered. One with 12 sensors at elbow locations, nozzles and long straight sections of pipe elements and another with only 8 sensors at elbow locations.

**IV.4 Signal Processing**

Vibrations based monitoring is used for a variety of civil engineering applications to detect changes which may indicate damage or degradation. Signal processing is a preliminary step within most health monitoring frameworks where the sensor response captured in the time-domain is transformed to the frequency domain using Fast-Fourier Transform (FFT) or power spectral density (PSD) algorithms, or the time-frequency domain using Short-Time Fourier transform (STFT), Hilbert-Huang transform (HHT), etc. This research focuses on FFT, PSD and STFT signal processing techniques along with the design of pattern recognition and feature extraction methodologies.
IV.4.1 Fast-Fourier Transform and Power Spectral Density

The acceleration-time series signals obtained from sensors installed on the piping system are converted to the frequency domain using FFT and PSD signal processing algorithms. In Part II of this dissertation, the efficiency of using PSD, instead of FFT, as a diagnostic tool is demonstrated. The acceleration-time series sensor response obtained from simulation tools such as FE analyses is stationary in nature. Therefore, its FFT, represented as $X(f)$, can be calculated and processed further to obtain the PSD, as given by Equation IV.1. Figure IV.4 illustrates a generic acceleration-time-series sensor response and its corresponding PSD in the frequency-domain.

$$PSD(f) = |X(f)|^2$$  \hspace{1cm} (IV.1)

Although the stationarity of signals (or time-series response) is assumed in most statistical procedures, the response obtained from a real-life structure would be non-stationary in nature and its FFT would not exist. Therefore, non-stationary signals are often transformed into stationary signals. A truncated FFT is implemented where the time-series response is integrated only over a finite interval of time, i.e. the overall response
is divided into various time windows. If the time-series response, x(t), is divided into N number of time windows, then the $PSD(f)$ can be calculated as the Fourier transform of the autocorrelation function, $R_{xx}$, in accordance with Equation IV.2.

$$PSD(f) = \sum_{n=0}^{N-1} R_{xx}(n)e^{-j2\pi nf}$$ (IV.2)

Part II and Part III of this dissertation is focused on calculating the PSD using Equation IV.1. However, in real-life applications and experiments, non-stationary sensor signals can be transformed to obtain the PSD using Equation IV.2. Currently, acquiring real-life signals and calculating PSD using Equation IV.2 is out of scope for the proposed condition monitoring framework and the research on this concept will be conducted as a future study. Once the PSD is acquired, the methodology presented in Part II and Part III can be utilized to extract a vector of degradation sensitive quantities to train the ANN algorithms. A sample vector of such quantities is tabulated in Table IV.1.

Table IV.1: Feature Extraction for a Vector with Four Quantities of Interest

<table>
<thead>
<tr>
<th>QoIs</th>
<th>Definition</th>
<th>Sample Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$PSD_{max}$</td>
<td>Maximum PSD amplitude from degraded response</td>
<td>$3.1E + 05$</td>
</tr>
<tr>
<td>$\Delta_{max}PSD$</td>
<td>Maximum difference observed in significant PSD peaks</td>
<td>$3%$</td>
</tr>
<tr>
<td>$\omega_{\Delta}$</td>
<td>Frequency corresponding to $\Delta_{max}PSD$</td>
<td>$17$ Hz</td>
</tr>
<tr>
<td>$PSD_{0,\Delta}$</td>
<td>non-degraded PSD peak corresponding to $\omega_{\Delta}$</td>
<td>$2.8E + 05$</td>
</tr>
</tbody>
</table>

IV.4.2 Short-Time-Fourier-Transform

In a nuclear facility, a continuous stream of sensor data can be acquired from accelerometers installed on the piping-equipment systems. However, in real-life applications, this continuous stream of data signals will typically be non-stationary in
nature. While the FFT can be calculated for stationary signals, such as those generated by simulation tools, it cannot be obtained for continuous non-stationary signals. In such cases, it becomes necessary to either obtain a truncated FFT of the signal over finite time intervals, or using other signal processing approaches which conserve the signals strength and resolution in the time and frequency domains, such as the STFT, HHT, Wavelet Transform, etc. This study focuses on using STFT on the sensor response obtained from simulations, to design a condition monitoring framework for nuclear piping-equipment systems subjected to earthquakes as well as normal operating vibrational loads.

The STFT is a transform algorithm related to the FFT, in which a non-stationary signal can be split into windows or fractions, such that the laws of stationarity in signals can be applicable within these timed windows. Then the Fourier transform can be computed for each of these windows following which, the varying spectrum as a function of time can be plotted to obtain the STFT. As illustrated in Figure IV.5, a typical one-dimensional acceleration-time-series sensor response is converted to a two-dimensional spectrum using the STFT algorithm.

![Figure IV.5: Short-Time Fourier Transform of Sensor Response](image-url)
After investigating the acquired STFT data from both the degraded system’s response and the non-degraded system’s response, it is observed that the magnitude of generated spectrum approaches zero after a frequency of 100 Hz. Therefore, to save on data storage resources, the STFT data is truncated to only provide a spectrum from 0 – 100 Hz of frequency. In order to achieve the best degradation-sensitive features, the difference in the STFT data obtained from the degraded system’s response versus the STFT data obtained from the non-degraded system’s response is evaluated and stored in a data repository, as illustrated in Figure IV.6.

**Non-Degraded State**

**Degraded State**

![2-D STFT Array Size 26 x 161](image)

**Figure IV.6: Extracting STFT data**

### IV.4.3 Data Storage and Processing

In this study, computationally effective data processing and storage techniques are also explored due to the large amount of data acquired from sensors on a nuclear piping-equipment system. For smaller datasets using a vector of four degradation sensitive quantities, a traditional .TXT file format is utilized. However for larger data...
sets including the complete time-series signal or the STFT of the signal, .TXT file format could not be used due to extensive processing times. Therefore, both the time-series signals and STFT data is consolidated into a Pickle file [137] for compact storage in the deep learning data repository. Pickle storage is chosen over Tensorflow Records [138] due to its efficiency and faster processing times for this particular application with nuclear piping-equipment systems. Table IV.2 demonstrates the different formats of data storage and processing used for training the ANN along with the number of data points acquired per uniaxial sensor.

Table IV.2: Data Storage and Processing Techniques

<table>
<thead>
<tr>
<th>Data processing</th>
<th>No. of data points per uniaxial sensor</th>
<th>Storage format</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-D acceleration-time series signal</td>
<td>20,475</td>
<td>Pickle File</td>
</tr>
<tr>
<td>1-D vector with 4 QoIs from PSD</td>
<td>4</td>
<td>.TXT File</td>
</tr>
<tr>
<td>2-D STFT array</td>
<td>26 × 161</td>
<td>Pickle File</td>
</tr>
</tbody>
</table>

IV.5 Deep Learning

Deep learning is a branch of machine learning in which artificial neural networks (ANNs) are developed and can be applied in many applications such as imaging classification, speech recognition, natural language processing, time-series classification and object tracking. The strength of deep learning algorithms lies in being able to model complex and non-linear inverse problems in order to predict outputs based on unseen test data. Deep learning algorithms can also perform feature extraction from raw data. However, large computational resources and time may be required for processing raw sensor data from nuclear piping-equipment systems. Therefore, this study compares the accuracy as well as the efficiency of deep learning algorithms with both processed and unprocessed
forms of input sensor data. Inspired by the biological neural networks, ANNs are made of a group of connected artificial neurons. Each neuron, as illustrated in Figure IV.7, takes an input value, processes it using an activation function and returns an output value to the connecting neurons. Before transmitting the input values through the activation functions, each input value is assigned an initial weight and then summed up with a bias term, as detailed in Equation IV.3.

\[
Output = f \left( \sum_{i=1}^{n} (w_i a_i) + b \right) = f(w_1 a_1 + w_2 a_2 + \cdots + w_n a_n + b)
\] (IV.3)

![Single Neuron Diagram](image)

Figure IV.7: Single Neuron

Multiple neurons are organized in interconnected layers, forming a web-like structure commonly referred to as the architecture of an ANN. The input layer consists of neurons carrying input information such as image pixel data, time-series signals, damage indices, etc., depending on the application problem being studied. The output layer consists of neurons carrying the predicted values. A feedforward neural network consists of a single layer of neurons between the input and output layer, called the hidden layer. The data is transported from the input layer to the output layer using only feedforward propagation algorithm. Based on the architecture of the ANN and statistical techniques used to process data, deep learning algorithms can be classified as feedforward neural networks, multilayer perceptron networks, convolutional neural networks, recurrent neural networks, autoencoders, restricted Boltzmann machine, Bayesian neural networks, etc. In this study, the effects of using multilayer perceptron networks versus convolutional neural networks are investigated along with the aforementioned signal processing techniques from section IV.4.
Multilayer Perceptron ANNs

Multilayer ANNs such as the multilayer perceptron network, with more than one hidden layer, utilize backpropagation algorithm in addition to the feedforward propagation algorithm, to transport data from the input layer to the output layer of the network. The first layer takes in the input data and the last layer produces output predicted values. The middle layers are called hidden layers since they are not accessible from outside the neural network. Each neuron in the hidden layer collects the output from all neurons in the previous layer, processes that data and transports it to the neurons of the next layer. The hidden layer functions as a distiller to locate and save important features from the input data. During the training of an ANN, a forward pass of the input data is accomplished in order to make a prediction. This prediction is compared to the real, expected output value by using a specified loss function. The error obtained in this process is then back-propagated through the network. Optimization algorithms such as Stochastic Gradient Descent (SGD), Adaptive Moment (Adam), Root Mean Square Propagation (RMSProp), Adaptive Gradient (AdaGrad), etc., are utilized to minimize this error, extract better features from the input data and calculate better weighted values for each of the neurons. In this study, the Adam optimizer is selected because of its ability to handle large datasets with computational efficiency [108]. A detailed study on the MLP ANN design, architecture and parameters has been demonstrated in Part II of this dissertation. Figure IV.8 illustrates the ANN used for predicting degraded locations and their degradation severity level using a vector of degradation sensitive quantities, for the simple-piping system.
IV.5.2 Convolutional Neural Networks

CNNs are a class of deep neural networks that can be used for various applications such as image classification and computer vision, with little or negligible data pre-processing. CNNs can be utilized over a large amount of sensor data without requiring prior knowledge or human interference in feature mapping. Despite their numerous advantages, implementing CNNs can be computational demanding and can necessitate the use of graphical processing units (GPUs) or even tensor processing units (TPUs) with high RAM specifications. In this research, both 1-D CNNs and 2-D CNNs are explored for the AI data-driven condition monitoring framework and their relative
performance and processing capabilities are compared. Similar to MLP ANNs, CNNs are made up of neurons contained in an input layer, at least one hidden layer, and an output layer. Although CNNs are specialized to work with 2-D image data, they can also be implemented on 1-D and 3-D input data sets. Contrary to MLP ANNs, CNNs contain at least one convolutional layer in its architecture that can perform “convolution” on the input data to extract a feature map. A convolutional layer of the CNN generates a feature map for the future layers of the network. Each subsequent layer is able to extract more complex features than the previous layer, thereby resulting in detection of more accurate degradation-sensitive data for the application of condition monitoring in nuclear piping-equipment systems.

As shown in Figure IV.9, the process of extraction to generate a feature map can be achieved by utilizing a filter across the input data. During the training process, the network is able to learn various filter parameters that can be specific to the type of application being explored. In field of deep learning, a filter is also commonly known as the kernel. For a 1-D CNN, a 1-D kernel is defined whereas for a 2-D CNN, a 2-D kernel is utilized across the the input data. The size of a kernel is typically smaller than the input data size so that important degradation-sensitive features can be extracted with precision. To aid the kernel in traversing the complete input data, a stride value is defined. Pooling layers can also be used to reduce the complexity of the convolutional network through dimensionality reduction. Two types of pooling layers can be implemented such as average pooling where the average of all values in a kernel is returned, or maximum pooling where the maximum of all values in a kernel is returned. In this study, the CNNs are designed with maximum pooling layers, which also work towards eliminating any overfitting of the data.
Figure IV.9: Convolution of Input Data

Once the higher level features containing information on the degraded state of the piping system have been extracted by the convolutional layers, the feature map is flattened and input into fully-connected layers at the end of the CNN. The layers used at the end of a CNN function like an MLP ANN to classify the data into an output prediction value. Some of the key parameters used for construction of the 1-D and 2-D CNNs in this study are tabulated in Table IV.3.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimizer</td>
<td>Adam</td>
</tr>
<tr>
<td>Epochs</td>
<td>2000 with early stopping criteria</td>
</tr>
<tr>
<td>Dropout</td>
<td>0.5</td>
</tr>
<tr>
<td>Activation Functions</td>
<td>PReLU: Convolutional Layer</td>
</tr>
<tr>
<td></td>
<td>Softmax: Output Layer</td>
</tr>
<tr>
<td>Validation split</td>
<td>30%</td>
</tr>
</tbody>
</table>

**1-D CNN architecture and hyper-parameter tuning**

In this research, various architectures and key parameters for a 1-D CNN as well as a 2-D CNN are explored as a part of the proposed condition monitoring methodology. For designing the 1-D CNN, training and hyper-parameter tuning is carried out by using the vector of degradation sensitive quantities from Part II of this dissertation. By varying the
number of convolutional layers, four different architectures of a 1-D CNN are analyzed as illustrated in Figure IV.10.

Hyper-parameter tuning is also demonstrated by incorporating numerous values for the learning rate of the model and batch size of the input data, as mentioned in Table IV.4, within each of the four 1-D CNN architectures being considered. The collection of data from high fidelity simulations, containing the vector of four degradation-sensitive quantities from each sensor response, is divided into training and testing data sets using 70% of the data for training and 30% for testing. From the training data set, 30% is used for validation of the various 1-D CNN architectures and hyper-parameters being evaluated. The models are trained over 2000 epochs with early stopping criteria for all the possible hyper-parameter combinations, and the validation accuracy obtained from each of these 1-D CNNs is tabulated in Table IV.4.
Figure IV.10: Designs of the 1-D CNN
### Table IV.4: Validation Accuracy for 1-D CNN

<table>
<thead>
<tr>
<th>Batch Size</th>
<th>Learning Rate</th>
<th>Validation Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.001</td>
<td>Design 1</td>
</tr>
<tr>
<td>8</td>
<td>0.001</td>
<td>91%</td>
</tr>
<tr>
<td></td>
<td>0.005</td>
<td>77%</td>
</tr>
<tr>
<td></td>
<td>0.01</td>
<td>68%</td>
</tr>
<tr>
<td>16</td>
<td>0.001</td>
<td>91%</td>
</tr>
<tr>
<td></td>
<td>0.005</td>
<td>77%</td>
</tr>
<tr>
<td></td>
<td>0.01</td>
<td>70%</td>
</tr>
</tbody>
</table>

From the validation accuracies, the overall performance of design 3 and design 4 is better than design 1 and design 2. The highest validation accuracy of 97% is observed for design 4 of the 1-D CNN with a learning rate of 0.001 and a batch size of 16. Hence, design 4 is selected for the 1-D CNN implementation in the proposed condition monitoring methodology. The plots for the training and validation accuracy versus the number of epochs is illustrated in Figure IV.11a. Similarly, the errors accumulated during the training and validation of the 1-D CNN network is shown in Figure IV.11b.
2-D CNN architecture and hyper-parameter tuning

2-D CNNs are designed to process two-dimensional image pixel data in the field of computer vision applications. This study explores the practicality of employing 2-D CNNs for time-series sensor data classification with respect to the condition monitoring of nuclear piping-equipment systems. The 2-D STFT data from the acquired sensor response is utilized for building a data repository containing key information on the piping system’s current degraded state [54]. Next, various architectures and hyper-parameters of the 2-D CNNs are trained and validated to select the best performing network. In this study, 5 architectures of the 2-D CNN are considered. The features of all the designs being investigated are tabulated in Table IV.5.
Table IV.5: Various 2-D CNN architectures

<table>
<thead>
<tr>
<th>Components</th>
<th>Design 1</th>
<th>Design 2</th>
<th>Design 3</th>
<th>Design 4</th>
<th>Design 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Convolutional Layers</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>No. of units</td>
<td>32</td>
<td>32</td>
<td>32</td>
<td>64</td>
<td>128</td>
</tr>
<tr>
<td></td>
<td>32</td>
<td>64</td>
<td>64</td>
<td>96</td>
<td>128</td>
</tr>
<tr>
<td></td>
<td>64</td>
<td>96</td>
<td>128</td>
<td>128</td>
<td></td>
</tr>
</tbody>
</table>

Figure IV.12: 2-D CNN Design

In order to find the most optimal hyper-parameters, a grid search is conducted on the values of the learning rate of the model as well as the batch sizes being fed into the network.

- Learning rate of the model: 0.001, 0.01
- Batch size of the input data: 128, 256, 512

An adaptive learning rate is implemented so that the value of learning rate could be decreased further whenever the network experienced a plateau in learning any new features from the provided input data. However, since using extremely low learning rates can result in a network with high computation cost, a lower bound on the learning rate is
incorporated as one-tenth of the provided learning rate value. Three dense fully connected layers containing 2048 neurons, 1024 neurons and the number of degraded locations for the final classification, respectively, are included in the architecture of the 2-D CNNs. All the 5 models are trained over 2000 epochs with early stopping criteria for all the possible hyper-parameter combinations, and the validation accuracy obtained from each of these 2-D CNNs is tabulated in Table IV.6.

Table IV.6: Validation Accuracy for 2-D CNN

<table>
<thead>
<tr>
<th>Batch Size</th>
<th>Learning Rate</th>
<th>Design 1</th>
<th>Design 2</th>
<th>Design 3</th>
<th>Design 4</th>
<th>Design 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>128</td>
<td>0.001</td>
<td>97%</td>
<td>99.4%</td>
<td>99.4%</td>
<td><strong>99.6%</strong></td>
<td>99%</td>
</tr>
<tr>
<td></td>
<td>0.01</td>
<td>96%</td>
<td>41%</td>
<td>96%</td>
<td>97%</td>
<td>20%</td>
</tr>
<tr>
<td>256</td>
<td>0.001</td>
<td>98%</td>
<td>99.5%</td>
<td>99.3%</td>
<td>99.3%</td>
<td>99%</td>
</tr>
<tr>
<td></td>
<td>0.01</td>
<td>96%</td>
<td>20%</td>
<td>36%</td>
<td>35%</td>
<td>30%</td>
</tr>
<tr>
<td>512</td>
<td>0.001</td>
<td>98%</td>
<td>99.3%</td>
<td>99.3%</td>
<td>99.2%</td>
<td>98%</td>
</tr>
<tr>
<td></td>
<td>0.01</td>
<td>96%</td>
<td>98%</td>
<td>34%</td>
<td>40%</td>
<td>31%</td>
</tr>
</tbody>
</table>

It is observed that almost all the designs being considered perform well with a learning rate of 0.001 when compared to a learning rate of 0.01. Overall, a batch size of 128 yielded in slightly better results. The best validation accuracy of 99.6% is obtained for a batch size of 128, learning rate of 0.001 and the 2-D CNN design 4. Therefore, this architecture of the 2-D CNN, illustrated in Figure IV.12, and hyper-parameter values are selected for further testing of the proposed condition monitoring framework. The plots for the training and validation accuracy and loss versus the number of epochs are shown in Figure IV.13.
IV.5.3 Model Fit Validation

The algorithms developed in the past decade for ANNs and deep learning applications have demonstrated numerous advantages in fields such as facial recognition, computer vision, autonomous control systems, digital twins, etc. However, one major statistical challenge of employing deep learning algorithms is the phenomenon of overfitting the data. When the network fits perfectly to the training data but is unable to predict accurately on unknown test data sets, the network might be plagued with the problem of overfitting. This means that the complexity of the network or non-sufficient shuffling of the data sets caused the neural network to overfit the training data, as shown in Figure IV.14 as an example. Overfitting can also be caused by noise in the data wherein the neural network learns on features extracted from noisy inputs. Additionally, a robust deep learning network should not underfit the data, wherein the network is unable to learn or predict effectively on any data set.
Many different techniques such as validation of the network, early stopping criteria, regularization, training with more data, augmentation of data, data preprocessing and feature extraction etc. have been proposed [139, 140, 141, 142, 143, 144] to counter this problem of overfitting the data. Acquiring more data for training the network and augmentation of data can be explored later when sensor response from experimental observations or real data from nuclear facilities is available. Part II and Part III of this dissertation are focused on the data preprocessing and feature extraction using the PSD to generate a vector of degradation-sensitive features, and in Part IV, the STFT from sensor response is extracted. The concept of early-stopping is also incorporated as one of the methods to keep the ANNs free from the phenomenon of overfitting, wherein the algorithm stops training if the model does not improve its performance after a certain number of epochs. For all the deep learning networks being investigated, the losses obtained when training the network are monitored for a total of 50 epochs before the early stopping criteria is implemented. While these seem like good solutions to combat overfitting, as illustrated in Figure IV.11 and Figure IV.13 which represent the losses incurred during training of the network versus number of epochs, additional steps described below are taken to ensure an optimal fit to the sensor data by the neural networks.

Validation of the networks is performed to generate an unbiased condition monitoring framework. In this study, two validation approaches called direct training-validation split and k-Fold validation split are demonstrated. In the
training-validation split, the sensor data obtained from high-fidelity simulations is randomized and then split as 70% for the training and 30% for the testing. From the data kept aside from training, another 30% is extracted for validation of the network’s performance. This method is utilized during the hyper-parameter tuning detailed in subsubsection IV.5.2 and subsubsection IV.5.2 and to select the best performing deep learning networks.

The k-Fold validation approach splits the entire data set into $k$ folds and then trains the network on $k - 1$ folds. The trained network is validated on the one fold that is left out during the learning phase. After conducting this process for all the combinations within the $k$ folds of the data, the average of all prediction accuracies is acquired as the final result. Since the complete data set is utilized for training and testing in different batches, the network is able to obtain an optimal fit for all output classifications. In this research, $k = 10$ folds are incorporated for implementing the k-Fold validation approach on the MLP ANN deep learning algorithm. The results from each fold are tabulated in Table IV.7.
Table IV.7: Accuracy from each fold in the k-Fold Validation

<table>
<thead>
<tr>
<th>Fold</th>
<th>Validation accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>96.6%</td>
</tr>
<tr>
<td>2</td>
<td>98.7%</td>
</tr>
<tr>
<td>3</td>
<td>98.1%</td>
</tr>
<tr>
<td>4</td>
<td>96.9%</td>
</tr>
<tr>
<td>5</td>
<td>98.7%</td>
</tr>
<tr>
<td>6</td>
<td>98.7%</td>
</tr>
<tr>
<td>7</td>
<td>98.1%</td>
</tr>
<tr>
<td>8</td>
<td>97.5%</td>
</tr>
<tr>
<td>9</td>
<td>97.5%</td>
</tr>
<tr>
<td>10</td>
<td>97.8%</td>
</tr>
<tr>
<td>Average</td>
<td>97.9%</td>
</tr>
</tbody>
</table>

The k-Fold validation is also implemented for the 1-D CNN as additional exploration. Table IV.8 demonstrates the validation accuracies obtained from both the validation approaches when applied to the MLP and 1-D CNN networks. It is observed that the k-Fold method results in best accuracies. However, the time taken to conduct k-Fold validation is significantly higher than the direct training-validation split method.
Another method to avoid overfitting is called regularization, in which some features from the input data set are penalized or eliminated, so that any noise in the input data set can be reduced. Using dropout values in the neural network is also a regularization technique, and this has been applied to all the networks designed in this research. Part II of this dissertation investigated the performance of an MLP ANN to various dropout values. In this study, the L1, L2 and L1,L2 regularization are implemented on the deep learning algorithms of MLP ANN and 1-D CNN. The function that generates losses from the predictions of the neural network is extended by a regularization term, as shown in Equation IV.4 for L1 regularization and in Equation IV.5 for L2 regularization, where $\alpha$ is called the rate of regularization, $W$ is the weighted matrix of the weight parameters in the neural network, and $L$ is the loss function. For L1,L2 regularization, both the approaches of L1 and L2 regularization are used to penalize the input parameter weights. In this study, the multiple values of $\alpha$ such as 0.1, 0.01 and 0.001 are explored before 0.001 is selected for the L1, L2 and L1,L2 regularization.

$$\hat{L} (W) = \alpha \| W \| + L (W)$$

(IV.4)

$$\tilde{L} (W) = \frac{\alpha}{2} || W ||^2 + L (W)$$

(IV.5)

From the results tabulated in Table IV.9, for the MLP ANN, it is observed that
using a dropout of 0.5 yields the best validation accuracy of 97%, while L2 regularization method gives the second highest validation accuracy of 93%. When regularization is implemented on the 1-D CNN algorithm, the dropout approach yields the highest accuracy of 97%. Since all the 4 regularization methodologies utilize similar computational resources, the dropout approach is selected based on its best performance for avoiding overfitting of the neural networks.

Table IV.9: Comparison of Regularization Approaches

<table>
<thead>
<tr>
<th>Type of DL Network</th>
<th>Regularization Approach</th>
<th>Validation Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLP ANN</td>
<td>Dropout</td>
<td>97%</td>
</tr>
<tr>
<td></td>
<td>L1</td>
<td>91%</td>
</tr>
<tr>
<td></td>
<td>L2</td>
<td>93%</td>
</tr>
<tr>
<td></td>
<td>L1_L2</td>
<td>89%</td>
</tr>
<tr>
<td>1-D CNN</td>
<td>Dropout</td>
<td>97%</td>
</tr>
<tr>
<td></td>
<td>L1</td>
<td>94%</td>
</tr>
<tr>
<td></td>
<td>L2</td>
<td>94%</td>
</tr>
<tr>
<td></td>
<td>L1_L2</td>
<td>79%</td>
</tr>
</tbody>
</table>
IV.6 Results and Discussion

The deep learning algorithms designed in section IV.5 are applied in conjunction with signal processing and feature extraction methodologies developed in section IV.4. The results obtained from implementing the proposed condition monitoring framework on case study 1, which represents the simple piping system subjected to seismic loads, are tabulated in Table IV.10. The effectiveness of using reduced sensors as per the sensor placement strategy proposed in Part II of this dissertation is demonstrated. The MLP ANN trained using a vector of 4 degradation-sensitive quantities extracted from 9 sensors on the system yields a 97% accuracy in predicting degraded locations and severity levels whereas a 96% accuracy is achieved when only 4 sensors are utilized. Since the prediction accuracy is almost the same, it can be beneficial to implement the proposed reduced sensor placement strategy in order to decrease the amount of data handling and use computational resources efficiently.

A 1-D CNN is also designed to be trained over the vector of 4 degradation-sensitive quantities extracted from the sensor’s PSD response. An accuracy of 95% is obtained by using the sensor data from either 9 sensors or 4 sensors from the simple piping system. Once again, these results build confidence in the reduced sensor placement strategy. In this application, even though the performance of a 1-D CNN versus an MLP ANN is almost similar, higher computational time is required to process data using 1-D CNN when compared to a simple MLP ANN. In both these cases, a 16Gb RAM with Central Processing Units is employed on a traditional desktop machine with 6 cores of Intel(R) Core(TM) i7-8700 CPU @ 3.2Ghz. Each epoch took about 1 second for the MLP ANN and about 3 seconds for training the 1-D CNN. The MLP ANN reached an optimal solution with about 220 epochs whereas 200 epochs are required for the 1-D CNN.
<table>
<thead>
<tr>
<th>Computational Resources</th>
<th>Type of DL Network</th>
<th>Training Parameters</th>
<th>Predict Locations</th>
<th>Predict Locations and Severity</th>
</tr>
</thead>
<tbody>
<tr>
<td>16Gb - CPU</td>
<td>MLP ANN</td>
<td>4 QoIs</td>
<td>97%</td>
<td>97%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>9 sensors</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>4 QoIs</td>
<td>96 %</td>
<td>96%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4 sensors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-D CNN</td>
<td></td>
<td>4 QoIs</td>
<td>96 %</td>
<td>95%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>9 sensors</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>4 QoIs</td>
<td>96 %</td>
<td>95%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4 sensors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>25Gb - TPU</td>
<td>2-D CNN</td>
<td>STFT</td>
<td>99.6%</td>
<td>97.3%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>9 sensors</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>STFT</td>
<td>99.7%</td>
<td>99.3%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4 sensors</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Next, a 2-D CNN is created and trained over a data repository containing the STFT data from the sensor responses. Significantly higher accuracies of 99% are achieved for predicting degraded locations by this procedure when compared to using the MLP ANN or the 1-D CNN with the proposed 4 quantities of interest (QoIs). Interestingly, it is observed that the 2-D CNN is able to achieve only 97% accuracy in predicting degraded locations as well as the severity level by using data from all 9 sensors on the system. This accuracy elevated to 99% with the proposed reduced sensor strategy. The justification in procuring a lower prediction accuracy with higher number of sensors can be attributed to the phenomenon of overfitting with large amounts of data. Overfitting can
reduce the predictive capability of any deep learning model. Although considerable efforts are taken to avoid overfitting in all of the models proposed in this research, the results prove that employing excessive redundant data from too many sensors can reduce the effectiveness of the 2-D CNN model with respect to the condition monitoring framework being investigated.

After examination of these results from the condition monitoring of a simple piping system, it can be said that the best performance is achieved by implementing a 2-D CNN trained on the STFT of the sensor’s acceleration-time series signals, along with a sensor placement strategy. However, this methodology utilizes significantly higher computational resources and time. When a 16Gb RAM with Graphical Processing Units is employed on a traditional desktop machine (6 cores of Intel(R) Core(TM) i7-8700 CPU @ 3.2Ghz, and GPU - NVIDIA GeForce GTX 1050), the training for each epoch took close to 30 minutes. To overcome this computational limitation, a cloud service with 25Gb RAM and Tensor Processing Units is employed to reduce the training time for each epoch to only 10 seconds. With such a setup, approximately 90 epochs are required for the training and testing of the 2-D CNN with 2-D STFT data. Since both the MLP ANN and the 2-D CNN yield a good prediction accuracy for degraded locations and the corresponding degradation severity, it can be recommended that depending on the available computational resources and time constraints at any nuclear facility, either of the two techniques proposed within the condition monitoring framework can be implemented.

Additionally, the 1-D CNN is analyzed and trained using the complete acceleration-time series signals from the sensors [3]. However, it must be noted that this analysis could not be completed even with the cloud computational services described above. An exorbitant amount of data is generated when the time-series data is utilized as-is rendering the deep learning model non-executable. Therefore, the feature extraction and signal processing techniques proposed in this research are beneficial in obtaining a well-desired
performance for the condition monitoring of nuclear piping systems in a post-hazard scenario.

Since nuclear equipment and connected piping systems can experience vibrations and fatigue failure even during normal operations, the methodologies designed for the simple piping system are applied to a second case study with the Z pipe system from the EBRII nuclear reactor. The Z pipe system is subjected to various vibrations, including harmonic excitations due to the auxiliary pump operations. A similar trend of results is observed when comparing the prediction accuracies illustrated in Table IV.10 to those shown in Table IV.11. On a traditional desktop machine, the MLP ANN with a database containing the proposed vector of 4 QoIs from only 4 reduced sensors achieved 97% accuracy in predicting degraded locations and severity levels whereas a 1-D CNN attained 96% accuracy for the same. The prediction accuracies saw a considerable increase to more than 99% by implementing a 2-D CNN learning from the STFT sensor data. However, similar to the post-hazard condition monitoring framework based on the simple piping system, the degradation assessment of the Z pipe system requires higher computational resources for the 2-D CNN when compared to the MLP ANN.
### Table IV.11: Results for EBRII Z pipe System

<table>
<thead>
<tr>
<th>Computational Resources</th>
<th>Type of DL Network</th>
<th>Training Parameters</th>
<th>Predict Locations</th>
<th>Predicted Locations and Severity</th>
</tr>
</thead>
<tbody>
<tr>
<td>16Gb - CPU</td>
<td>MLP ANN</td>
<td>4 QoIs</td>
<td>99%</td>
<td>97%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>12 sensors</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>4 QoIs</td>
<td>98 %</td>
<td>97%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>8 sensors</td>
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<td>1-D CNN</td>
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<td>25Gb - TPU</td>
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### IV.7 Conclusions

Advanced nuclear reactors with autonomous control systems hope to enable safe nuclear operations whilst aiming for clean energy production. Nuclear power facilities are made up various structures and systems, such as piping systems, which connect the advanced reactor to multiple other equipment and vessels. This study explores the performance of a condition monitoring framework for nuclear piping-equipment systems that can experience degradation due to flow-assisted corrosion and erosion over the course of time. Deep learning techniques are utilized to build the AI data-driven monitoring framework.
Three types of deep learning algorithms, such as MLP ANN, 1-D CNN and 2-D CNN, are designed and tested for predicting degraded locations as well as the degradation severity in nuclear piping-equipment systems subjected to post-hazard scenario and normal operating loads. The key conclusions of this research are:

- The acceleration-time series signals collected from sensors, such as accelerometers, installed on real-life structures and systems are usually non-stationary in nature. The FFT is applicable only for stationary signals, unless it can be applied in conjunction with the concept of timed windows, commonly known as the STFT. Therefore, in this study, the sensor data collected from high fidelity simulations on nuclear piping systems is converted to the 2-D STFT format in the frequency and time domain. This can be applicable to more realistic sensor signals collected from advanced nuclear reactors. The robust diagnostic capability of utilizing the STFT data as degradation-sensitive features is demonstrated in this research.

- Convolutional networks such as the 1-D CNN and the 2-D CNN are investigated for time-series classification of data. Due to computational complexity of using 2D CNNs along with STFT data, cloud computing resources are employed for the training and testing of the framework. To avoid overfitting of the deep learning model to the training data, different approaches such as early stopping criteria, validation, regularization and feature extraction are demonstrated and compared for obtaining an optimal fit to the sensor data repository.

- The performance of convolutional networks in comparison to MLP ANNs is analyzed. The 2-D CNN model almost always achieved accuracies of more than 99% for both the piping systems being considered. The MLP ANN performed slightly better than the 1-D CNN. In the absence of high computational power, this study recommends the use of MLP ANN with a vector of degradation sensitive quantities for scenarios such as post-hazard, where information on the degraded state of the plant is required urgently. For the real-time condition monitoring of the nuclear piping and equipment
systems, the 2-D CNN with STFT sensor data is recommended as the best option with the highest prediction accuracies for the degraded locations and severity levels.
PART V

Summary, Conclusions, and Recommendations for Future Research
V.1 Summary and Conclusions

This dissertation presents an artificial intelligence based condition monitoring framework for nuclear safety systems, such as piping-equipment systems. It includes three main manuscripts that focus on describing the following key topics:

- Post-Hazard Condition Assessment of Nuclear Piping-Equipment systems using ANNs
- AI Driven Condition Monitoring of Nuclear Piping-Equipment systems under Normal Operating Loads
- Assessment of Deep Learning Algorithms for the Condition Monitoring of Nuclear Piping-Equipment Systems

The summary and conclusions for each of these topics are given below:

V.1.1 Post-Hazard Condition Assessment of Nuclear Piping-Equipment systems using ANNs

A major earthquake at a nuclear power plant requires a careful and detailed assessment of the structural integrity of plant’s SSCs. This study is aimed at creating an artificial intelligence driven framework for the condition assessment of nuclear equipment and piping. A simple 3-dimensional piping-equipment system is selected as an application case study for developing the proposed approach. The sensor response is converted from an acceleration-time series signal to its power spectral density (PSD). It is shown that PSD is a powerful diagnostic quantity for detecting all levels of degradation, including minor degradation, in complex distributed systems. It contains information about the system’s current state and corresponding dynamic characteristics. Then, a realistic nuclear piping-equipment system is considered for testing the efficacy of the framework proposed in this research. It is observed that high levels of accuracy at 99% can be achieved in
predicting the degraded locations as well as the severity levels. The key conclusions of the study are summarized as follows:

- The applicability of physics-based models can be sensitive to the type of structure/system being monitored. Considering a single damage index as the degradation-detection feature can result in a loss of response from lower order modes of vibration in piping systems. For nuclear piping-equipment systems, pattern recognition is necessary to extract optimum information from the sensor data. It is shown that using only one quantity of interest, such as the maximum peak PSD value, results in an inadequate diagnostic database as the contribution to the response from multiple modes of interest may be lost. 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 are extracted.

- The effects of sensor placement are studied for the simple pipe system and a strategy is developed. The effectiveness of the proposed sensor placement strategy is illustrated by applying it to the complex piping-equipment system. It is observed that the quality of data obtained after reducing the number of sensors is still sufficient for training the ANN framework. Studying the effects of sensor placement can be beneficial in reducing computational and economic costs incurred due to large amounts of data-processing from numerous triaxial sensors.

- The proposed condition assessment framework is able to detect degraded locations along with the severity in degradation as minor, moderate or severe. Detecting cracks in nuclear systems is representative of major damage which can lead to nuclear accidents. Hence, detection of minor degradation in such systems can be quite effective. This study also incorporates uncertainty in the degradation severity levels to illustrate that the assessment framework is quite effective even when such uncertainties are present.
• Deep learning algorithms can be extremely helpful in processing a vector of degradation-sensitive features extracted from the sensor data. After training and testing the architecture and various key parameters for the deep learning algorithms, significant accuracy is achieved in predicting potential degraded locations as well as degradation severity in the simple piping system. To check the efficacy of the proposed ANN framework, it is applied to a reactor coolant loop piping-equipment systems and a 99% accuracy is achieved in detecting degradation locations and the corresponding severity levels.

It is shown that with the help of modern AI techniques and data processing, degradation in distributed systems, such as nuclear equipment and piping systems, can be monitored efficiently. While this study is quite preliminary and exploratory in nature, it provides a strong foundation for enhancing it further and for potentially testing it using actual measured sensor data.
V.1.2  AI Driven Condition Monitoring of Nuclear Piping-Equipment systems under Normal Operating Loads

Critical vibrations caused by pressure pulsations in the fluid due to pump operations can cause cracks and leakages in nuclear piping systems. Generally, these vibrations result in high-cyclic fatigue failure which is difficult to detect with current NDT techniques and scanning processes prevalent in the nuclear industry. This study is aimed at developing an AI based condition monitoring framework that can detect degraded locations along with their degradation severity level for a nuclear piping-equipment system. For the case study, the Z-pipe system from EBRII nuclear reactor is considered and subjected to the auxiliary pump-induced vibrations. The acquired sensor response is converted to an acceleration-time series signal, and then the PSD is extracted as the degradation-sensitive tool. It is observed that the proposed condition monitoring framework is able to detect degraded locations and their severity with 97% accuracy for the Z-pipe system. The proposed methodology is also extended to include a strategy based assessment on the pump operating speeds in order to avoid fatigue build-up due to pump-induced vibrations.

The key conclusions of the study are summarized as follows:

- The pattern recognition and feature extraction technique proposed in Part II of this dissertation is applied to a piping-equipment system subjected to vibrations due to normal pump operations. In Part II, the proposed methodology demonstrates good results for a piping system subjected to a post hazard scenario, with the power spectral density containing multiple unique peaks. In contrast, the power spectrum, obtained from the sensor response of a piping system subjected to normal operating loads, is observed to be smooth with fewer peaks. In spite of this characteristic difference in the captured power spectral density, the proposed condition monitoring methodology is able to extract well-defined degradation-sensitive features.

- It is shown that using a vector of degradation-sensitive quantities is better than
using a single degradation-sensitive quantity, since the vector can capture essential features from all modes of vibration in piping systems. A loss of response from lower order modes of vibration can occur if a single quantity is used for creating the ANN training database.

- A deep learning algorithm using an MLP ANN is designed along with a sensor placement strategy for predicting degraded locations in the EBRII nuclear reactor’s Z-pipe system. Using this algorithm and a reduced sensor placement strategy, the condition monitoring methodology is able to detect degradation due to flow-assisted erosion and corrosion with 98% accuracy.

- The importance of detecting degradation severity level along with the degraded location is demonstrated since different locations can experience varying intensities of degradation severity. The proposed methodology achieved a 97% accuracy in predicting the degraded locations and classifying the corresponding level of severity as minor, moderate and major. Uncertainty in these classifications levels is also considered by assuming a uniform distribution with a lower and upper bound for each of the levels.

- An in-depth analysis of the erroneous predictions is carried out to gain an insight into the performance of the deep learning network. It is found that about only 2% of the total test cases predicted locations that were far from the actual location experiencing degradation.

- An enhancement to the proposed condition monitoring framework is demonstrated by including a strategy based assessment to avoid high-cyclic fatigue at hot spot degraded locations of the piping system. An application example is presented for the Z-pipe system which compares stresses at degraded locations to the ASME design criteria for fatigue. Two potential recommendations are specified on safe pump operational speeds as well as the allowable number of cycles or hours the pump can be operated at certain speeds, before fatigue can cause cracking and leakage failure.
in the piping system.

V.1.3 Assessment of Deep Learning Algorithms for the Condition Monitoring of Nuclear Piping-Equipment Systems

Advanced nuclear reactors with autonomous control systems hope to enable safe nuclear operations whilst aiming for clean energy production. Nuclear power facilities are made up various structures and systems, such as piping systems, which connect the advanced reactor to multiple other equipment and vessels. This study explores the performance of a condition monitoring framework for nuclear piping-equipment systems that can experience degradation due to flow-assisted corrosion and erosion over the course of time. Deep learning techniques are utilized to build the AI data-driven monitoring framework. Three types of deep learning algorithms, such as MLP ANN, 1-D CNN and 2-D CNN, are designed and tested for predicting degraded locations as well as the degradation severity in nuclear piping-equipment systems subjected to post-hazard scenario and normal operating loads. The key conclusions of this research are:

- The acceleration-time series signals collected from sensors, such as accelerometers, installed on real-life structures and systems are usually non-stationary in nature. The FFT is applicable only for stationary signals, unless it can be applied in conjunction with the concept of timed windows, commonly known as the STFT. Therefore, in this study, the sensor data collected from high fidelity simulations on nuclear piping systems is converted to the 2-D STFT format in the frequency and time domain. This can be applicable to more realistic sensor signals collected from advanced nuclear reactors. The robust diagnostic capability of utilizing the STFT data as degradation-sensitive features is demonstrated in this research.

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training and testing of the framework. To avoid overfitting of the deep learning model to the training data, different approaches such as early stopping criteria, validation, regularization and feature extraction are demonstrated and compared for obtaining an optimal fit to the sensor data repository.

- The performance of convolutional networks in comparison to MLP ANNs is analyzed. The 2-D CNN model almost always achieved accuracies of more than 99% for both the piping systems being considered. The MLP ANN performed slightly better than the 1-D CNN. In the absence of high computational power, this study recommends the use of MLP ANN with a vector of degradation sensitive quantities for scenarios such as post-hazard, where information on the degraded state of the plant is required urgently. For the real-time condition monitoring of the nuclear piping and equipment systems, the 2-D CNN with STFT sensor data is recommended as the best option with the highest prediction accuracies for the degraded locations and severity levels.
V.1.4 Recommendations for Future Research

Based on the experience gained in conducting this research, it is suggested that further research should consider the following aspects:

- Enhance the proposed condition monitoring framework to detect degradation at multiple locations of the nuclear piping-equipment system simultaneously.
- Conduct validation of the proposed condition monitoring framework by performing experiments in the laboratory to collect sensor response data from real piping systems.
- Consider data augmentation algorithms as well as noise handling techniques to eliminate any noise, such as White noise, Gaussian noise, or environmental noise, in the acquired sensor data.
- Extract a vector of degradation sensitive quantities from the STFT data to reduce the amount of data storage capacity required by the deep learning algorithms. Compare its diagnostic capability against using the complete STFT data.
- Explore the use of recurrent neural networks (RNNs) to generate any missing sensor response data due to sensor malfunctioning.
- Further investigate sensor placement strategies to design an optimal sensor mapping methodology that can capture the most degradation-sensitive features from the entire piping-equipment system.
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