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CONDITION MONITORING OF NUCLEAR EQUIPMENT-PIPING USING DEEP LEARNING

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ABSTRACT

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. Nuclear safety systems can undergo vibrations due to various normal operating loads such as pump operations, flow-induced, water hammer, acoustical resonance, etc. Over the course of time, safety systems such as piping-equipment systems experience degradation due to flow-accelerated erosion and corrosion. Undetected degradation at hot-spot locations can be subjected to a build up of cyclic fatigue due to operational vibrations and thermal cycles. To avoid fatigue and subsequent cracking, a condition monitoring framework is required for the detecting degradation. This paper demonstrates the use of sensor data, feature extraction and Artificial Neural Networks (ANNs) in designing a condition monitoring framework for a nuclear piping-equipment system subjected to pump-induced vibrations during normal operations. The proposed framework also incorporates uncertainty in the degradation severity classifications, such as minor, moderate or severe. For the application case study, a piping system from Experimental Breeder Reactor II nuclear reactor is selected. It is observed that a high prediction accuracy is achieved when detecting degraded locations and their severity classification. Additionally, a strategy based-assessment methodology is illustrated via an application example to provide recommendations for "safe" pump speeds and allowable number of cycles, as per ASME design criteria, to avoid fatigue in equipment and connected piping systems due to pump-induced vibrations.

INTRODUCTION

Operations and maintenance costs comprise about 60 to 70% of the overall generating cost in legacy light water nuclear power plants (Wacker, 2007). The current practice involves performing maintenance of safety systems through performance trending and maintenance practices, and of passive components through aging management programs (U.S.NRC, 2010). 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 (Wu, 1989). Therefore, it is important to identify and retrofit any degraded locations to address the operational functionality of the nuclear safety systems. 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 (Lee and Kim, 2021; Lin et al., 2022, 2021b; Wood et al., 2017) 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 (Lin et al., 2021a; NAMAC, 2018). 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. 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 (American Society of Mechanical Engineers Boiler and Pressure Vessel Committee, 2015) can provide strategic assessments, such as safe pump speeds and allowable number of cycles, to the maintenance operators.

Sandhu (2021) highlights the limitations of extending existing health monitoring studies (Alamdari et al., 2017; Erazo et al., 2019; Martini et al., 2015; Rezaei and Taheri, 2010; Rosafalco et al., 2020; Zhang and Sun, 2021) 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. It seems like a vector of damage-sensitive quantities might be a better degradation-sensitive quantity 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. Additionally, 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 (Saran et al., 2019). 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.

This research focuses on three important aspects: (i) Extracting a novel vector of degradation sensitive quantities from the sensor data to detect even minor degradation in nuclear piping-equipment systems. (ii) Detecting degraded locations as well as their degradation severity by designing a deep learning neural network and a sensor placement strategy (iii) Proposing a strategy based-assessment methodology for recommending "safe" pump operational speeds, to avoid high-cycle fatigue build up in the nuclear piping systems, 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.

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 (Jacimovic and D'Agaro, 2019). 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 discontinuities of piping safety systems (Gupta et al., 2021; Ju and Gupta, 2015; Ryu et al., 2016). Therefore, a condition monitoring framework is designed by using a part of the piping-equipment system from EBRII (Davis et al., 1970; Lin et al., 2021a; Sumner and Wei, 2012) coolant system called 'Z-pipe' system shown in Figure 1a. The Z-pipe system is subjected to vibrational loads due to normal pump operations. Stress concentrations at detected degraded sections of the Z-pipe system are determined and checked against the allowable ASME design criteria (American Society of Mechanical Engineers Boiler and Pressure Vessel Committee, 2015) to provide a scenario-based recommendation for safe pump operating speeds.

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 vibration as shown in Figure 1b. These steady-state vibrations can be harmonic with a force amplitude and excitation frequency, as shown in Equation 1.

$$f(t) = F\sin(\omega_f t) \text{ or } F\cos(\omega_f t) \tag{1}$$

where, $f(t)$ is the harmonic excitation load, F is the force amplitude and ω_f is the excitation frequency in radians/second. The excitation frequency ω_f varies with the speed of pump operations, as shown in Equation 2 (Gao et al., 2020; Qing et al., 2006).

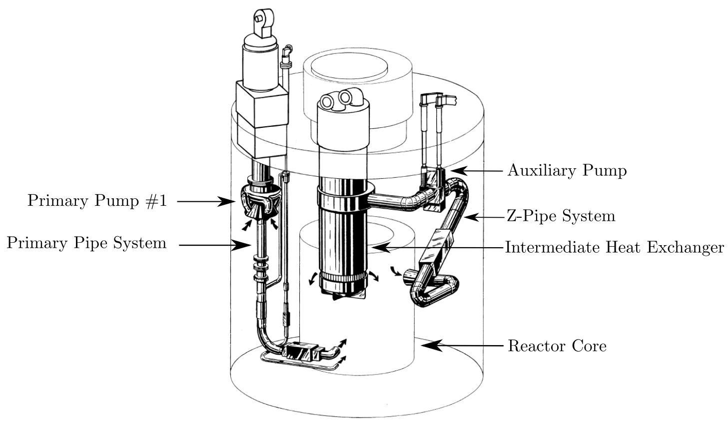
$$\omega_f = 2\pi\frac{nNP}{60} \tag{2}$$

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.

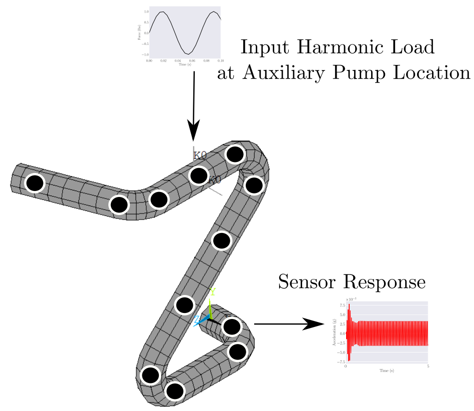
As a part of this proof-of-concept condition monitoring framework, the auxiliary pump is assumed to operate between 620 rpm (rotations per minute) and 1000 rpm. Therefore, from Equation 2, the excitation frequency range for pump-induced harmonic vibrations can be calculated as $10 - 17$ Hz. A steady-state 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 1b.

Degradation and Uncertainty

Nuclear piping-equipment systems experience degradation in the form of pipe-wall thinning due to flow-assisted erosion and corrosion (Wu, 1989). 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. 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. 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. 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 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 (Bodda et al., 2020a,b, 2019, 2020c, 2016; Sandhu, 2015).



(a) EBRII Primary Tank Layout (Sumner and Wei, 2012)



(b) Z-pipe system

Figure 1. EBRII and Z pipe system

SIGNAL PROCESSING AND FEATURE EXTRACTION

The condition monitoring framework is first implemented by converting the acquired acceleration-time series sensor response to it power spectral density (PSD) in the frequency domain. In this study, PSD is used as a potential degradation-sensitive quantity of interest. 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, feature extraction is implemented to obtain 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 I of this dissertation over using a single degradation-sensitive quantity as the training feature for the AI algorithms. A representative vector for a typical sensor response has been tabulated in Table 1.

Table 1: Feature Extraction: Four Quantities of Interest

QoIs	Definition	Sample Values
PSD_{max}	Maximum PSD amplitude from degraded response	199.42
$\Delta_{max}PSD$	Maximum difference observed in significant PSD peaks	6.55%
ω_{Δ}	Frequency corresponding to ΔPSD_{max}	13.57 Hz
$PSD_{0,\Delta}$	non-degraded PSD peak corresponding to ΔPSD_{max}	161.08

DEEP LEARNING AND PROPOSED CONDITION MONITORING FRAMEWORK

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. 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, Sandhu (2021) 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 research focuses on applying the previously proposed deep learning algorithm to piping-equipment systems subjected to vibrational operating loads.

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 2 illustrates the results obtained from testing the proposed framework for the various aforementioned feature extraction techniques, sensor placement formulations and MLP ANN architectures.

Table 2: Accuracy of Proposed Condition Monitoring Framework

Model	**Predict Locations**	**Predict Locations and Severity**
12 Sensors Training Feature: PSD_{max}	86%	74%
12 Sensors Proposed Vector of Training Features	99%	97%
8 Sensors: Proposed Sensor Placement Strategy Proposed Vector of Training Features	98%	97%

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 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.

STRATEGY BASED ASSESSMENT FOR AVOIDING FATIGUE

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) (American Society of Mechanical Engineers, 2020) 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.

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. An example flowchart of the strategy based assessment is shown in Figure 2.

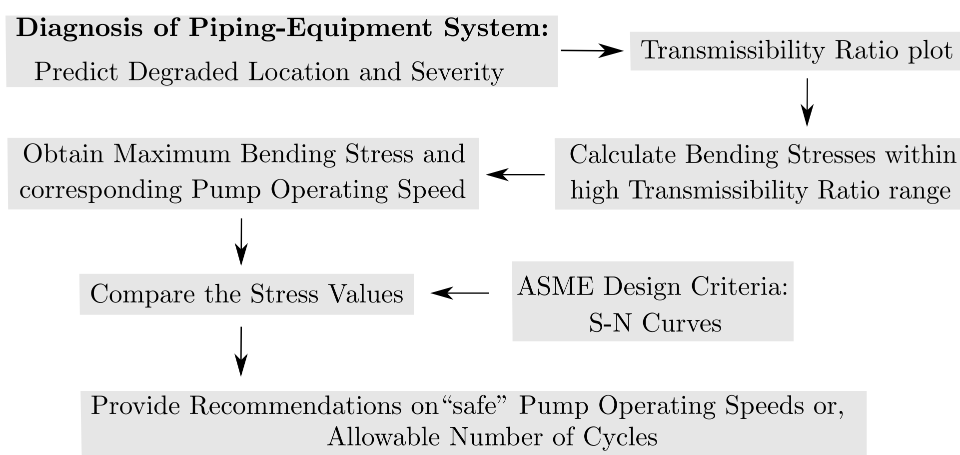


Figure 2. Strategy Based Assessment Flowchart

The proposed condition monitoring framework is utilized to detect any degraded locations on the Z-pipe system along with its degradation severity. Next, a transmissibility ratio plot is generated for the degraded location subjected to various auxiliary pump operating speeds and corresponding frequencies of excitation. From this transmissibility ratio plot, the range of frequencies with the highest transmissibility ratio values are selected. 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.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. In this hypothetical example, the maximum bending stress at Nozzle 1 of the Z-pipe system is found to be 22 ksi at 14.7 Hz of excitation frequency. This excitation frequency is equivalent to an auxiliary pump operating speed of 882 RPM from Equation 2.

The ASME BPVC II (American Society of Mechanical Engineers Boiler and Pressure Vessel Committee, 2015) 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 3 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. In this hypothetical example, it can be shown that a maximum number of 3×10^5 cycles can be obtained for 22 ksi allowable stress value from the ASME S-N Curve illustrated in Figure 3.

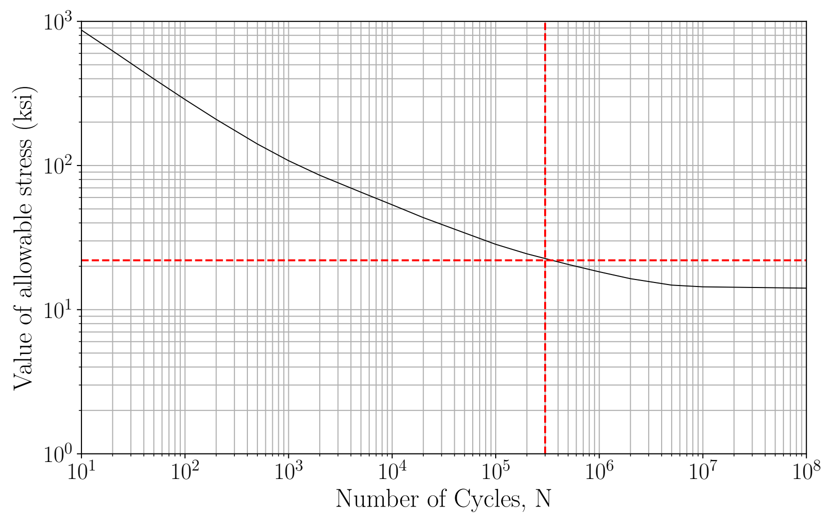


Figure 3. ASME S-N Curve for Type 304 Stainless Steel Pipe Material (American Society of Mechanical Engineers Boiler and Pressure Vessel Committee, 2015)

The final step is to provide a strategy-based 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 3.

$$\text{Allowable hours, } h = \frac{\text{Number of cycles from SN curve}}{\text{Pump speed in RPM} \times 60} = \frac{3 \times 10^5}{882 \times 60} = 5.6 \text{ hours} \tag{3}$$

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. The key conclusions of the study are summarized as follows:

- 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 to detect degradation due to flow-assisted erosion and corrosion with 98% accuracy.
- The importance of detecting degradation severity 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 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.

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