Development of Digital Twin Predictive Model for PWR Components: Updates on Multi Times Series Temperature Prediction Using Recurrent Neural Network, DMW Fatigue Tests, System Level Thermal-Mechanical-Stress Analysis

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Nuclear Science and Engineering Division

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ABSTRACT

The long-term operation (LTO) of nuclear power plant (NPP) beyond their original design life of 40 years, can lead to more material damage associated with cyclic fatigue under thermal-mechanical loading cycles and associated long-term exposure of reactor material to the deleterious reactor-coolant environments. However, under this LTO condition the reactor components can still safely operate but may require more frequent Nondestructive Evaluation (NDE) of reactor components. Frequent NDE requirement may lead to frequent shutdown of the NPP. This in turn can lead to power outage and additional NDE-inspection-cost related economic loss. The economic loss can be minimized by reducing uncertainty in life estimation of safety-critical pressure boundary components and by implementing more digital approach such as by using upcoming digital-twin (DT) technology for predicting the structural states (e.g., time and location dependent inside/outside thickness temperature, stress, strain, plastic deformation, etc.) and associated fatigue life of a component in real time. Towards this goal Argonne National Laboratory (ANL) with the sponsorship of DOE Light Water Reactor Sustainability (LWRS) program is working on the development of a DT framework that can be used for real time environmental fatigue prediction of reactor components. The DT framework is based on limited experiment-data, Artificial-intelligence (AI) – Machine-Learning (ML) - Deep-Learning (DL) based techniques and Multiphysics-computational-mechanics such as finite element (FE) based modeling tools. Towards this overall goal, following are some of the major contributions made during the FY21:

- 1) Multiple 82/182 dissimilar metal weld (DMW) specimens (both solid-weld and joint-weld representing the actual reactor multi-metal nozzles) were fatigue tested. The resulting fatigue lives were compared to the NUREG-6909 based best-fit and design fatigue curves. Additionally, the results of 52/152 DMW fatigue specimens (which were recently tested at Republic of Korea under the sponsorship of International Nuclear Energy Research Initiative - INERI program) were compared to the NUREG-6909 based best-fit and design fatigue curves. From the comparison of 82/182 and 52/152 DMW test data with NUREG-6909 best-fit curve, most of the reported test data fall way away from the NUREG-6909 suggested best-fit or mean curve. The NUREG-6909 suggested best-fit curve is the best-fit curve of austenitic stainless steel and due to lack of enough data on Nickel-based welds, this is currently being used for predicting the life of Nickel-alloy-based welded components. However, the above observation may require higher scaling factor (e.g., ASME suggested factor of 20 on cycles rather than the current NUREG-6909 suggested factor of 12 on cycles) for scaling the austenitic-stainless-steel best-fit-curve for estimating the design or safe-life of a welded component. Accordingly, for example, if a DMW component experience a strain amplitude of 0.6% the PWR-water life of the component would be 52 cycles instead of 85 cycles. However, more DMW tests are required to further ascertain the above-mentioned observations.
- 2) A system level CAD and finite element model were developed which consists of reactor pressure vessel (RPV), part of steam generator (SG), part of pressurizer (PRZ), hot leg (HL), and surge line (SL). This is with detailed nozzle geometry and thermal-mechanical material properties of different metals to simulate realistic thermal-mechanical stress under connected system global thermal-mechanical boundary conditions.
- 3) Different system level heat transfer analyses were performed with estimation of relevant heat transfer coefficients. The resulting data were used in subsequent system level thermal-mechanical stress analysis and for generating spatial-temporal training and validation data for a system level digital-twin based temperature predictor. Transient heat transfer analyses were performed

considering thermal boundary condition under design-basis (DB) loading and EDF (Électricité de France) data-based grid-load-following (EDF-GLF) loading cycles.

- 4) System level thermal-mechanical stress analysis was performed for identifying damage-prone hotspots and for future extension of the model for cyclic state prediction. From the system-level model simulation under DB loading cycle it is found that HL and the SL nozzle that connect to the HL can experience significant stress and strain and could be one of the weakest links in the overall reactor coolant system (RCS).
- 5) An AI/ML based DT model was developed for multi-time-series temperature prediction at any inside/outside thickness locations of PWR pressure boundary components. This is by using Recurrent-neural-network (RNN) and keras machine learning libraries. The RNN model was validated against two laboratory test-based data sets with one obtained through ANL's in-air fatigue test system and other through PWR-water test loop. The experimentally validated DT model further validated against FE model results to predict thermal scarification related spatial-temporal temperatures at random locations of a component. The well validated DT model was then used for demonstrating spatial-temporal temperature prediction under 100+ years of reactor operation subjected to combined DB, EDF-GLF and randomized grid-load-following (RANDOM-GLF) loading Cycles. The expert-elicitation DT model framework was developed assuming field/input/process measurements can be available from a few existing plant sensors and can readily be used by the NPP operators. The above temperature prediction model will feed to the next-step stress analysis model based on which the life of a component can be predicted in real-time, which is one of our future works.

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ABBREVIATIONS

AI	Artificial Intelligence
ANL	Argonne National Laboratory
ASME	American Society of Mechanical Engineers
CL	Cold Leg
DL	Deep Learning
DMW	Dissimilar Metal Weld
DOE	Department of Energy
ET	Elevated Temperature
FE	Finite Element
HAZ	Heat Affected Zone
HL	Hot leg
LAS	Low Alloy Steel
LWR	Light Water Reactor
LWRS	Light Water Reactor Sustainability
ML	Machine Learning
PRZ	Pressurizer
PWR	Pressurized Water Reactor
RCS	Reactor Coolant System
RNN	Recurrent Neural Network
RPV	Reactor Pressure Vessel
SG	Steam Generator
SL	Surge Line
SMW	Similar Metal Weld
SS	Stainless Steel

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1 Introduction

Accurate and real-time structural integrity prediction of nuclear reactor components is important for safe and long-term economic operation of the US nuclear reactor fleet. Among different approaches of component life estimation three methods are quite popular for assessing the structural integrity of safety-critical structural components. These are Safe-life, Fail-safe, and Damage-tolerance approaches.

A component designed under *safe-life* approach is assumed not to fail under the stated operating load and within a stated period called the design life. The benefits of safe-life designs include reducing the likelihood of unplanned maintenance and reducing the likelihood of any catastrophic failure. Under the safe-life approach, a design load is selected by considering a safety factor with respect to the ultimate load-carrying limit of a component. In general, most of the operating LWRs inside and outside the US are designed for a life of 40 years. Also, most of the pressure-boundary components of these reactors are originally designed with a safe-life assumption such that they are anticipated not to fail at all or to have a very low failure probability. However, owing to economic considerations, the LWR fleet needs to operate beyond its original design life of 40 years. With this need in mind, the basic requirement of safe-life design to restrict the operation of the reactor to its maximum design life is violated. When the safe-life criterion is violated, then the question arises whether those reactors are now safe to operate. That question leads to the discussion of fail-safe and damage-tolerance criterion.

A component designed under **fail-safe** conditions is designed to remain safe in the event of a failure. A fail-safe design does not prevent failure but withstand failure when it does occur. For example, in the context of the aerospace industry, an example is the minimum requirement of two engines and multiple load paths for commercial aircraft. When the aircraft is airborne, if one engine fails, the aircraft can still fly and land using the second engine. Similarly, with multiple load paths, if a structural element of an aircraft fails, the airplane can still fly and land because the load can be transferred to other load-carrying members. In that context, a nuclear reactor component that has already exceeded the above mentioned safe-life limit of 40 years and is still operating can be considered as an example of a fail-safe component. This is true for a component without or with the presence of a detectable crack much smaller than the critical length (at which the component would completely or catastrophically fail). For a component with undetectable cracks, the material of the component might have degraded (because it has already passed the initial safe-life limit of 40 years), but not enough to show any visual sign of failure, and the component can still survive many years of operation. Similarly, if detectable cracks are present but are much smaller than the critical length, the component can still survive many years of operation with/without minor repair. The USNRC's approach to extend the license of some LWRs from 40 years to 60 years can be considered as an example of rebranding a pressure-boundary component from safe-life to fail-safe. Under fail-safe conditions, the probability of detecting a crack during a routine inspection, before it could progress to catastrophic failure, is very high. A fail-safe regime allows the safe operation of a component up to a maximum detectable defect size (also known as the allowable damage limit).

In other hand, a *damage-tolerance* approach assumes that flaws can be present in any structure and can propagate with usage or under operating loadings and environments, but the component can still be operated safely. However, the damage-tolerance approach emphasizes rigorous inspections to detect flaws before they can progress to critical limits. Damage tolerance requires an inspection regime (e.g., through offline and intermittent **Nondestructive Evaluation or NDE**) tailored to the flaw progression characteristics of a particular component under the expected loading spectrum and environment.

Damage tolerance places a much higher emphasis on a frequent inspection regime to detect flaws before they progress to critical or unsafe limits, whereas a fail-safe approach allows cracks to grow to obvious and easily detected dimensions.

When the reactors will be operated for much longer time (say 80 or 100 years) compared to the original design life of 40 years, more cracking of component is expected due to the long-term exposure of reactor material to the deleterious reactor-coolant environment. That means some of the safety-critical components will fall into fail-safe and damage-tolerance regime requiring more frequent inspections of the components. This in turn requires frequent shutting down of the NPP for NDE inspection. However, the economic loss associated with frequent shutting down related power outage and additional NDE inspection related cost can negatively impact the overall economic performance of NPP operators. For this reason, NPP operators are increasingly looking for **online monitoring (OLM)** of plant components. However, one of the major drawbacks of the OLM based plant inspection technique is that it requires to place many sensors at different locations of the component for accurately estimating the state of that component. In an NPP, it is not that easy to place sensors at the required locations. This is because of the survival of the sensors in harsh radiation environment, difficulty in making new port for insertion of sensor and its instrumentation, stringent regulatory requirement of qualifying any sensor for NPP use, etc. One of the approaches to avoid this difficulty is the use of upcoming **digital-twin (DT)** technology. The DT model is a combination of online monitoring, artificial-intelligence-machine-learning (AI/ML) and physics based twin model of the actual component, that can be used for expert elicitation of spatial-temporal component states even there are few online measurement sources (such as few existing plant sensors currently being used for process or plant thermohydraulic measurements) currently available.

We are developing a DT framework specifically targeted towards predicting the structural states (e.g., time and location dependent inside/outside thickness temperature, strain, stress, plastic deformation, etc.) and associated fatigue life of a component at any given time. Towards this overall goal we update the following works in this FY-21 report:

- a) **Section-2:** Updates on the fatigue testing of dissimilar metal weld and the comparison of resulting fatigue lives with NUREG-6909 based best-fit and design strain versus life curves.
- b) **Section-3:** Finite element model-based system level heat transfer analysis for subsequent system level thermal-mechanical stress analysis and generating spatial-temporal training and validation data for a system level digital-twin based temperature predictor.
- c) **Section-4:** Finite element model-based system level thermal-mechanical stress analysis for damage-prone hotspot identification and for future extension of the model for cyclic state prediction.
- d) **Section-5:** AI/ML-Recurrent-neural-network based digital-twin model development for multi-time-series temperature prediction at any inside/outside thickness locations of PWR pressure boundary components.

2 DMW specimen Fabrication, Fatigue Experiments and Comparison of Life Data to NUREG-6909 Strain versus Life Curves

In this section, updates on DMW specimen fabrication, 82/182 DMW fatigue test results and their comparison with NUREG-6909 strain versus life curves are presented. In addition, summary of the 52/152 DMW fatigue test results (which were recently conducted at Republic of Korea under the International Nuclear Energy Research Initiative: INERI program) are presented.

2.1 Fabrication of DMW Solid-weld, Multi-metal-joint and HAZ Specimens

Recently we have fabricated different along the weld (solid weld), across the weld (multi-metal-joint) and heat-affected-zone (HAZ) specimens from an already welded SS-LAS DMW plate. Figure 2.1 shows the fabricated DMW plate cut into different blocks for fatigue specimen fabrication. Figures 2.2 and 2.3 show the cross-section locations of along the weld (solid weld) or along the rolling direction (of HAZ region) and cross-section locations of across the weld (multi-metal-joint) specimens. Total 10 solid-weld, 10 LAS-HAZ, 12 SS-HAZ specimens were fabricated from block-1 and 2 of the DMW plate. The block-3 of the DMW plate was used for fabricating 18 multi-metal-joint specimens. The intention of the solid-weld and HAZ specimens are for conducting fatigue tests for understanding material degradation mechanism and material properties estimation (for physics-based model). Whereas intention of the multi-metal-joint specimens are for conducting fatigue tests that mimics the actual reactor nozzle which has similar multi-metal-joints. Figure 2.4 shows the geometry of the hourglass-type specimens for both the solid-weld and multi-metal-joint specimens.

Figure 2. 1 Fabricated DMW plate cut into different blocks for fatigue specimen fabrication.

Figure 2. 2 Cross-section locations of along the weld (solid weld) or along the rolling direction (of HAZ region) of the fabricated specimens.

Figure 2. 3 Cross-section locations of across the weld of the fabricated DMW multi-metal-joint specimens.

Figure 2. 4 Geometry of hourglass-type specimens.

2.2 Different 82/182 DMW Fatigue Test Cases and the Observed Fatigue Lives

We have conducted fatigue tests of both solid-weld and multi-metal-joint specimens. The reported tests were primarily conducted under direct strain-controlled condition except ET-F61 and EN-F62 test case which were conducted under pseudo-strain-controlled condition [1]. Table 2.1 gives the summary of test environment, loading and observed fatigue life of different 82/182 DMW solid or joint weld specimens. All the tests were conducted with a strain rate of 0.01%/s and for different strain amplitudes of 0.3, 0.4, 0.5 and 0.6 %.

Table 2. 1 Summary of test environment loading and observed life for 82/182 solid welds/joints.

Test ID	Material	Environment	Strain amplitude (%), rate (%/s), and $R = \frac{\varepsilon_a^{min}}{\varepsilon_a^{max}}$	Fatigue life (Cycles)
DMW solid-weld (or along the weld) specimens				
*LWRS/ ET-F59	Solid-weld (182 Butter)	In-air, 300 °C	Strain amplitude = 0.6%, strain rate = 0.01%/s, and R = -1	2984
*LWRS/ ET-F61	Solid-weld (82 Filler)	In-air, 300 °C	Strain amplitude = 0.6%, strain rate = 0.01%/s, and R = -1	1133
LWRS/ ET-F63	Solid-weld (182 Butter)	In-air, 300 °C	Strain amplitude = 0.5%, strain rate = 0.01%/s, and R = -1	1335
LWRS/ ET-F64	Solid-weld (182 Butter)	In-air, 300 °C	Strain amplitude = 0.4%, strain rate = 0.01%/s, and R = -1	10480
LWRS/ ET-F65	Solid-weld (182 Butter)	In-air, 300 °C	Strain amplitude = 0.3%, strain rate = 0.01%/s, and R = -1	9896
*LWRS/ EN-F62	Solid-weld (82 Filler)	PWR-water, 300 °C	Strain amplitude = 0.6%, strain rate = 0.01%/s, and R = -1	842
DMW joint (or across the weld) specimens representing actual reactor nozzles				
LWRS/ ET-F66	Weld-joint	In-air, 300 °C	Strain amplitude = 0.6%, strain rate = 0.01%/s, and R = -1	1169
LWRS/ ET-F67	Weld-joint	In-air, 300 °C	Strain amplitude = 0.5%, strain rate = 0.01%/s, and R = -1	835
LWRS/ ET-F68	Weld-joint	In-air, 300 °C	Strain amplitude = 0.4%, strain rate = 0.01%/s, and R = -1	5585
LWRS/ ET-F69	Weld-joint	In-air, 300 °C	Strain amplitude = 0.3%, strain rate = 0.01%/s, and R = -1	1036

* Tests were conducted in earlier FY and some of the related results can be found from our earlier publications [1].

2.3 Different 52/152 DMW Fatigue Test Cases Conducted (Conducted at Republic of Korea under INERI program) and the Observed Fatigue Lives

Argonne National Laboratory is in a collaboration agreement with Republic of Korea under the International Nuclear Energy Research Initiative (INERI) program. While ANL focuses on 82/182 DMW fatigue tests, Korean counterpart focuses on 52/152 welds primarily used for weld repair. The aim of the collaboration is to share the fatigue test data of the 82/182 and 52/152 DMWs. Table 2.2 presents the summary of test environment loading and observed fatigue life for Korean conducted 52/152 DMW fatigue tests. This is using both along the weld (solid-weld) or across the weld (multi-metal-joint) specimens.

Table 2. 2 Summary of test environment loading and observed life for 52/152 solid welds/joints.

Test ID		Weld	Environment	Strain amplitude (%), rate (%/s), and $R = \frac{\varepsilon_a^{min}}{\varepsilon_a^{max}}$	Fatigue life (Cycle)
Fatigue	MAH351-1	Solid-weld (52 Filler)	In-air 300 °C	0.35 %, 0.1 %/s, and R = -1	20275
	MAH501-1			0.5 %, 0.1 %/s, and R = -1	2373
	MAH501-2				3779
	MAH501-3				3831
	MAH651-1			0.65 %, 0.1 %/s, and R = -1	1472
	MAH651-2				1367
	MPH501-1	PWR-water 300 °C	0.5 %, 0.1 %/s, and R = -1	3838	
	MAH500-1	In-air 300 °C	0.5 %, 0.01 %/s, and R = -1	4969	
	BAH501-1		0.5 %, 0.1 %/s, and R = -1	4969	
	BAH501-2			4543	
	BAH501-3			955	
	BAH701-1		0.7 %, 0.1 %/s, and R = -1	699	
	BAH701-2			602	
	JAH501-1		Weld-joint	0.5 %, 0.1 %/s, and R = -1	1032
	JAH501-2				1412
	JAH701-1			0.7 %, 0.1 %/s, and R = -1	701
	JAH701-2				832

2.4 Comparison of DMW-Fatigue-Specimen Lives with NUREG-6909 Based Best-fit and Design Lives

We compared the NUREG-6909 [2] based best-fit and design fatigue curves with the observed DMW-fatigue-specimen lives. This is to check where the 82/182 and 52/152 test data stand with respect to both best-fit (or mean) and design strain versus life curves. To note that the mean curve is directly based on the test data and is the best-fit representation of the test data. However, due to scatter (associated with material variability, surface finish, size difference between test specimen and actual components) in test data, ASME code suggest using the design curve to estimate the fatigue life of actual components. The design curves have been obtained based on the best-fit curves but by scaling the mean fatigue life by either a factor of 2 on strain or 20 on life or cycles, whichever is more conservative [3]. These factors of 2 and 20 are not safety margins but rather adjustment factors that should be applied to the small-specimen data to obtain reasonable estimates of the lives of actual reactor components. In addition, the above factors doesn't include the effect of specific coolant environment that could substantially reduce the life of component. The NUREG-6909 based environmental correction factor (F_{en}) is to further adjust the estimated design life of reactor components. Furthermore, with absence of adequate data for constructing separate best-fit and design curves for alloy 600 and other Ni-Cr-Fe metals (including welds e.g. 82/182 welds), NUREG-6909 suggest to use the strain versus in-air life (steel $\epsilon_a \sim N_a$) curves of austenitic stainless steel. Also, to note that the NUREG-6909 expression for stainless steel best-fit $\epsilon_a \sim N_a$ curve is very similar as the Tsutsumi best-fit curve given in Japan Nuclear Energy Safety Organization (JNES) report [4]. The expression for the NUREG-6909 (refer to Eq. 29 of [2]) and Tsutsumi $\epsilon_a \sim N_a$ curve (refer to Figure E-3.3.2-1 of [4] for equivalent expression) are respectively given in Eq. (1) and Eq. (2) as below:

$$\ln(N_a) = 6.891 - 1.920 \ln(\epsilon_a - 0.112) \quad (2.1)$$

$$\ln(N_a) = 6.861 - 2.1882 \ln(\epsilon_a - 0.11) \quad (2.2)$$

Note that Eq. (1) and Eq. (2) represent the mean or best-fit curves. Using the Eq. (1) and Eq. (2), the expression for strain amplitude versus life ($\epsilon_a \sim N_w$) mean-curve, under PWR-water environment can be found as below:

$$\begin{aligned} \ln(N_a) &= A - B \ln(\epsilon_a - C) \\ \text{Or } \ln(F_{en} * N_w) &= A - B \ln(\epsilon_a - C) \\ \text{Or } \ln(N_w) + \ln(F_{en}) &= A - B \ln(\epsilon_a - C) \\ \text{Or } \ln(N_w) &= A - B \ln(\epsilon_a - C) - \ln(F_{en}) \end{aligned} \quad (2.3)$$

Based on Eq. (2.1) the values of constants A, B, and C in Eq. (2.3) are 6.891, 1.920 and 0.112, respectively. However, according to NUREG-6909 [2] the expression for F_{en} in Eq. (2.3) is as below:

$$F_{en} = \exp(-T^* \epsilon^* O^*) \quad (2.4)$$

In Eq. (2.4) T^* , ϵ^* , and O^* are transformed temperature, strain rate, and dissolved oxygen (DO), respectively. According to NUREG-6909, the functional forms for these transformed parameters for Ni-Cr-Fe alloys are as follows:

$$\begin{aligned} T^* &= 0 && ; (T < 50^\circ\text{C}) \\ T^* &= (T-50)/275 && ; (50^\circ\text{C} \leq T \leq 325^\circ\text{C}) \\ \epsilon^* &= 0 && ; (\dot{\epsilon} > 5.0\%/s) \\ \epsilon^* &= \ln(\dot{\epsilon}/5.0) && ; (0.0004\%/s \leq \dot{\epsilon} \leq 5.0\%/s) \\ \epsilon^* &= \ln(0.0004/5.0) && ; (\dot{\epsilon} < 0.0004\%/s) \\ O^* &= 0.06 && ; (\text{NWC BWR water (i.e., } \geq 0.1 \text{ ppm DO)}) \\ O^* &= 0.14 && ; (\text{PWR or HWC BWR water (i.e., } < 0.1 \text{ ppm DO)}) \end{aligned} \quad (2.5)$$

Inserting the expression for F_{en} from Eq. (2.4) in Eq. (2.3), the expression for best-fit (or mean) strain amplitude versus life curve under PWR-water environment ($\epsilon_a \sim N_w$) can be rewritten as below:

$$\ln(N_w) = A - B \ln(\epsilon_a - C) + T^* \epsilon^* O^* \quad (2.6)$$

Using the Eqs. (2.1) and (2.2) we have plotted both the NUREG-6909 and Tsutsumi best-fit in-air curves. We have also plotted the corresponding NUREG-6909 design curves considering a strain factor of 2, life factors of 12 and 20. Figures 2.5 and 2.6 show the comparison of in-air design curves against the corresponding in-air best-fit or mean curves for strain amplitude and life based scaling, respectively. Note that NUREG-6909 (refer to section 3.2.11 of [2]) states that the current ASME Code Section III requirement for a factor of 20 on cycles to account for the effects of material variability and data scatter, specimen size, surface finish, and loading history is conservative by at least a factor of 1.7. Therefore, to reduce this conservatism, NUREG-6909 suggests mean-stress-adjusted curve by a factor of 2 on strain/stress and 12 on cycles, whichever was more conservative. The factor of 12 suggestion was made based on the vast amount of austenitic SS in-air test data. However as shown in Figures 2.5 and 2.6 it can be seen that most of the test data (both 82/182 and 52/152 DMW test cases) fall way away from the NUREG-6909 suggested best-fit air curve of austenitic stainless steel. This is particularly true that most of the observed test points fall left of the best-fit curve. That means should we have enough weld test data, the resulting best-fit or mean curve (specific to welded metals) would fall left of the current suggested best-fit curve. On other hand this means a lower best-fit or mean life of welded component. Furthermore, not all the 82/182 DMW joint data fall within the design curves factor of 2 on strain/stress and 12 on cycles. Although the above observation was based on limited data overall, there is a possibility of under prediction of fatigue lives of welded components and requires higher scaling factor e.g., a factor of 20 on predicted life/cycle (as originally suggested by ASME code). With the above observations we suggest using the design curve constructed with factor of 20 on cycles rather than factor of 12 on cycles. Despite considering a factor of 20 on cycles, from Figure 2.6 it can be still seen that one

joint specimen (out of the total four 82/182 DMW joint specimens tested) data falls outside the in-air design curve (constructed with factor of 20 on cycles). More fatigue tests of the joint specimens (both under in-air and coolant-water conditions) are required to further characterize the fatigue behavior of welded components. In addition, effect of the mean-strain (actual reactor component are in general subjected to stain cycles with substantial mean strain), intermittent small-amplitude cycles and strain rate need to be assessed.

In addition to the in-air curves, we have also constructed the PWR-water design curves, which was estimated from in-air design curves but with a further factor of environmental correction factor (Fen) on life or cycles. The comparison of these curves with respect to the corresponding in-air design curves and test data can be found from Figure 2.5 and 2.6. The corresponding numerical comparisons for different strain amplitudes under in-air and PWR-water conditions are presented in Tables 2.3 and 2.4, respectively. Note that a strain rate of 0.0004 %/s (the limiting case up to which the NUREG-6909 based Fen can be estimated) was assumed for estimating the Fen (= 3.75), based on which the PWR-water design curves were constructed. Table 2.4 give comparison of maximum possible design life both considering a strain rate of 0.01 %/s (Fen = 2.39) and strain rate of 0.0004 %/s (Fen = 3.75). From the Table 2.4 for certain loading conditions (e.g., strain amplitude of 0.6%), **the design life under PWR-water can be as low as 52 cycles.**

Figure 2. 5 Test data comparison with respect to best-fit and design strain versus life curves (with strain amplitude factored by 2).

Figure 2. 6 Test data comparison with respect to best-fit and design strain versus life curves (with life factored by 12 and 20)

Table 2. 3 Summary of the NUREG-6909 based best-fit and design in-air lives for different strain amplitudes and their comparisons with 82/182 DMW test data.

Strain amplitude (%)	No. of cycles based on Nureg-6909 best-fit life based on SS mean air curve: N_a	No. of cycles based on Nureg-6909 air-design life scaled by factor of 12 on cycles $N_d = \frac{1}{12} N_a$	No. of cycles based on Nureg-6909 air-design life scaled by factor of 20 on cycles: $N_d = \frac{1}{20} N_a$	No. of cycles based on LWRS 300°C, air fatigue test: 82/182 DMW solid weld	No. of cycles based on LWRS 300°C, air fatigue test: 82/182 DMW joint weld
0.3	23851	1988	1193	9896	1036
0.4	10480	873	524	10480	5585
0.5	5996	500	300	1335	835
0.6	3868	322	193	2984	1169

Table 2. 4 Summary of the NUREG-6909 based best-fit and design PWR-water lives for different strain amplitudes and their comparisons with 82/182 DMW data.

Strain amplitude (%)	No. of cycles based on Nureg-6909 best-fit life based on SS mean water curve: $N_w = \frac{1}{F_{en}} N_a$ (for strain rate = 0.0004 %/s) (for strain rate = 0.01 %/s)	No. of cycles based on Nureg-6909 water-design life scaled by factor of 12 on cycles & F_{en} : $N_{w,d} = \frac{1}{12 * F_{en}} N_a$ (for strain rate = 0.0004 %/s) (for strain rate = 0.01 %/s)	No. of cycles based on Nureg-6909 water-design life scaled by factor of 20 on cycles & F_{en} : $N_{w,d} = \frac{1}{20 * F_{en}} N_a$ (for strain rate = 0.0004 %/s) (for strain rate = 0.01 %/s)	No. of cycles based on LWRS 300°C, water fatigue test: 82/182 DMW solid weld	No. of cycles based on LWRS 300°C, water fatigue test: 82/182 DMW joint weld
0.3	6360 (9980)	530 (832)	318 (499)	NA	NA
0.4	2824 (4431)	235 (369)	141 (222)	NA	NA
0.5	1599 (2509)	133 (209)	80 (125)	NA	NA
0.6	1031 (1619)	85 (135)	52 (81)	$N_w = 842$, strain rate 0.01 %/s	NA

2.5 DMW Solid-weld Versus Multi-metal-joint Stress Hardening Behavior

The final fatigue failure (and the associated fatigue life) of a component is not a sudden end-of-life event, rather depends on the cyclic evolution of underlying stress/strain. Hence, it is important to understand and characterize the cyclic evolution of stress/strain of both DMW solid-weld and multi-metal-joints. Figures 2.7 to 2.10 show the comparison of observed cyclic-stress-amplitudes for 82/182 DMW solid-weld and joint specimens fatigue tested under different strain amplitudes. Although these figures don't show any pattern (whether solid-weld or joint specimens show higher hardening stress), component with higher hardening stress might experience higher deleterious effect under coolant environment.

Figure 2. 7 DMW solid-weld vs joint specimen observed cyclic stress amplitudes for fatigue test cases with a strain amplitude of 0.3%, with test conducted at in-air 300°C.

Figure 2. 8 DMW solid-weld vs joint specimen observed cyclic stress amplitudes for fatigue test cases with a strain amplitude of 0.4%, with test conducted at in-air 300°C.

Figure 2. 9 DMW solid-weld vs joint specimen observed cyclic stress amplitudes for fatigue test cases with a strain amplitude of 0.5%, with test conducted at in-air 300°C.

Figure 2. 10 DMW solid-weld vs joint specimen observed cyclic stress amplitudes for fatigue test cases with a strain amplitude of 0.6%, with test conducted at in-air 300°C .

3 Finite Element Based System Level Heat Transfer Analysis Under Design-Basis & Grid-Load-Following Loading

In this section, we discuss a finite element (FE) based system level heat transfer model to simulate spatial-temporal temperature of a reactor component. Resulting temperature prediction can be used in a stress analysis model to estimate the spatial-temporal thermal strain and corresponding stress contributions. The overall aim is to predict the stress states in the hot-leg (HL) and surge-line (SL) and in their dissimilar metal weld (DMW) nozzles. Unlike a traditional single component-based model, in the reported work we propose a system level model for more accurately imposing the system level thermal-mechanical boundary conditions associated with system level thermal gradients and displacements (or strains). The details of the model and associated heat transfer analysis results are discussed below.

3.1 Finite Element Model

In the proposed system level model, a 2-loop PWR was considered as an example case. Figure 3.1 shows the schematic of a typical 2-loop PWR and its associated primary and secondary loop components. The primary-loop of a typical 2-loop PWR consists of reactor pressure vessel (RPV), steam generator (SG), pressurizer (PRZ), hot leg (HL), cold leg (CL), surge-line (SL) and coolant pump (CP). Our primary aim was to simulate stress and strain in primary pressure boundary components such as HL and SL under realistic connected system thermal-mechanical boundary conditions. For this reason, only the components (such as RPV, SG and PRZ), that are directly connected to HL and SL were modeled in the proposed system level model. Since the HL and SL is at a height from the bottom of the RPV, we considered the entire RPV geometry. Whereas, for SG and PRZ only the bottom-head of SG and PRZ were modeled since the HL or SL is connected at the bottom head of SG or PRZ. The bottom-heads of RPV, SG and PRZ was applied with a fixed displacement boundary conditions assuming they are skirt supported with top part of the skirt welded to the bottom-head of RPV or SG or PRZ, and the bottom part of the skirt bolted to the ground pedestal. However, the actual reactor boundary conditions can be way different and can vary from plant to plant. Nevertheless, our aim is to develop a methodology for system-level digital-twin development and eventually replicate the concepts in actual nuclear plant for real time thermal-mechanical stress/strain prediction at any given locations and time. Figure 3.2 shows the assembly level CAD model of RPV, bottom head of SG, bottom head of PRZ, HL, SL and their DMW nozzles. Individual nozzles of the HL and SL were modeled in detail with both dissimilar metal weld (DMW) and similar metal weld (SMW). The DMW connects the 508 LAS of nozzle to the 316 SS of HL or SL safe ends. Whereas the SMW connects the 316SS safe-end of nozzle to the 316SS HL or SL pipe. Figures 3.3 and 3.4 show the CAD model and different materials of HL and its nozzles and the associated FE mesh, respectively. Whereas Figures 3.5 and 3.6 show the CAD model and different materials of SL and its nozzles and the associated FE mesh, respectively.

Figure 3. 1 Schematic of a typical 2-loop PWR and associated primary and secondary loop components (figure source US NRC website [5])

Figure 3. 2 Assembly level CAD model of RPV, bottom head of SG and PRZ, HL, SL and their DMW nozzles.

Figure 3. 3 CAD model and different materials of HL and its nozzles.

Figure 3. 4 FE mesh of HL and its nozzles.

Figure 3. 5 CAD model and different materials of SL and its nozzles.

Figure 3. 6 FE mesh of SL and its nozzles.

3.2 Material Properties and Heat Transfer Coefficients

Thermal properties for both metal and water are required for a component heat transfer analysis. Metal thermal properties such as, thermal conductivity and specific heat were taken from section II D of the 2017 version of the American Society of Mechanical Engineers' (ASME's) pressure vessel and piping code [6]. The thermal properties considered were for material types that are the same as or very similar to those used in the discussed system level FE model. For example, the properties of SA-508 were used for modeling the 508 LAS (used for RPV, SG, PRZ and all the nozzles), while the properties of 304SS were used for modeling the nozzle SMW and SS cladding. The thermal properties of Inconel[®] alloy In-600 were used for modeling the DMW filler and butter welds in the nozzle model. In addition to the thermal properties of metals, it is also required to know the water thermal properties such as temperature-dependent density, dynamic viscosity, and specific heat. These are required for estimating heat transfer coefficients at different boundary surfaces. The thermal properties of water were taken from IAEA report [8]. The heat transfer coefficients were estimated at various thermal boundary surfaces using the following equation for Nusselt number (Nu).

$$Nu = \frac{hD_h}{k^w} \quad (3.1)$$

In Eq. (3.1), h , D_h , and k^w are the heat transfer coefficient, hydraulic diameter, and thermal conductivity of water, respectively. The Nusselt number (Nu) in Eq. (3.1) can be further expressed as:

$$Nu = 0.023(Re_{D_h})^{0.8}(Pr)^{0.4} \quad (3.2)$$

In Eq. (3.2), Re_{D_h} , and Pr are the Reynold's and Prandtl numbers, respectively and can be estimated using the following expressions:

$$Re_{D_h} = \frac{\rho^w V D_h}{\mu^w} \quad (3.3)$$

$$Pr = \frac{\mu^w C_p^w}{k^w} \quad (3.4)$$

In Eqs. (3.3 and 3.4), ρ^w , μ^w , C_p^w , and V are the density, dynamic viscosity, specific heat, and water velocity, respectively. The water velocity at a particular temperature can be estimated given the information of mass flow rate, water temperature, hydraulic diameter, and density of water at that temperature. For example, for estimating the water velocity in hot leg and cold leg we assumed reactor coolant system (RCS) flow rate per loop = 89,000 gpm [8]. Whereas for estimating the water velocity in surge-line we considered a maximum mass flow rate of 50 gpm assuming very slow flow of water in SL. Assuming the maximum temperature condition (in individual components), and the associated water properties (ρ^w , μ^w , C_p^w), the corresponding Reynold, Prandtl and Nusselt numbers and the heat transfer coefficients were estimated. The maximum-temperature-condition heat transfer coefficients were applied to the various thermal boundary surfaces for conducting the heat transfer analysis. Table 3.1 shows the example estimated typical fluid characteristics at the different thermal boundary surfaces. We also modeled the interface conductance [9] between the respective supports and HL or SL. Note, the

inside shell of the RPV was modeled with same heat transfer coefficient as that estimated for CL assuming both will experience similar ID temperature.

Table 3. 1 Example estimated typical fluid characteristics at the different thermal boundary surfaces.

	ID of CL	ID of HL	ID of SL (near HL)	ID of SL (Mid-section)	ID of SL (Near PRZ)
Maximum Temperature (°C)	287.78	326.4	326.4	343.82	347.3
Reynold's number	5.22e7	7.71e7	1.20e5	1.25e5	1.26e5
Prandtl number	0.8793	1.0915	1.0915	1.3353	1.4296
Nusselt number	32618	48615	275.64	308.02	318.39
Convective heat transfer coef. (W/m ² K)	32981	30433	477.86	489.76	496.38

3.3 Thermal Boundary Conditions

Transient heat transfer analysis of the overall assembly was performed by applying transient (time-dependent) temperature boundary conditions to the various thermal boundary surfaces. Two heat transfer models were developed: One considering the design-basis (DB) loading cycle and the other considering the EDF (Électricité de France) data [10] based grid-load-following (EDF-GLF) loading cycle. The DB loading cycle-based heat transfer analysis results were later used in stress analysis model (refer section 4) and training the AI/ML based model (refer section 5). Whereas the EDF-GLF loading cycle-based heat transfer analysis results were later used in testing/validating the AI/ML based model (refer section 5). Figure 3.7 shows the applied temperature transients at the ID surfaces of HL, CL (or RPV) and PRZ. Figure 3.8 shows the applied pressure transients at the ID surfaces of all the primary-loop components i.e., of RPV, HL, SL, PRZ and bottom-head of SG. Only the bottom-head of SG was modeled representing the primary HL and CL sides. Note that the feed water or secondary side will have different temperature transients if the complete SG to be modeled. Different temperature boundary conditions were applied to the different sections of SL to simulate a transient thermal stratification condition. For example, the ID surfaces of the SL divided into seven different sections and applied with seven assumed temperature transients. However, to note that for more accurate temperature boundary conditions, it is required to perform the CFD analysis under both design-basis-loading and grid-load-following loading, which is not only out-of-scope of this report, but also extremely computationally intensive (due to time scale associated with full reactor cycle with time more than a full year). Nevertheless, the boundary-temperature-transients for the individual sections of SL were estimated by

scaling the temperature of HL and PRZ at any given time and were estimated based on the following time-dependent expressions:

$$\theta_{s1} = \theta_{HL} \quad (3.5)$$

$$\theta_{s2} = \theta_{HL} + \frac{1}{6}(\theta_{PRZ} - \theta_{HL}) \quad (3.6)$$

$$\theta_{s3} = \theta_{HL} + \frac{2}{6}(\theta_{PRZ} - \theta_{HL}) \quad (3.7)$$

$$\theta_{s4} = \theta_{HL} + \frac{3}{6}(\theta_{PRZ} - \theta_{HL}) \quad (3.8)$$

$$\theta_{s5} = \theta_{HL} + \frac{4}{6}(\theta_{PRZ} - \theta_{HL}) \quad (3.9)$$

$$\theta_{s6} = \theta_{HL} + \frac{5}{6}(\theta_{PRZ} - \theta_{HL}) \quad (3.10)$$

$$\theta_{s7} = \theta_{PRZ} \quad (3.11)$$

In Eqs. (3.5 to 3.11) $\theta_{si=1,2..7}$ are the time-dependent temperature boundary conditions applied to the different ID surface of SL pipe and its nozzle assembly. Whereas θ_{HL} , and θ_{PRZ} are the time-dependent temperature boundary conditions applied to the ID surface of HL and PRZ (refer Figure 3.7). In addition to the heat transfer analysis under design-basis-loading, heat transfer analysis was also performed under the grid-load-following loading condition. Figure 3.9 shows the EDF data-based Grid-load-Following power fluctuation [10] profile that was used for generating the input wall temperature for HL and CL/RPV. Whereas Figure 3.10 shows the simulated ID wall temperature of PRZ, HL, RPV or CL under grid-load-following power operation (with heat-up and cool-down conditions maintained similar as the design-basis loading cycle, refer Figure 3.7).

Figure 3. 7 Temperature boundary conditions applied to the inner wall of PRZ, HL, RPV and CL side of SG with magnified view during a) start b) end of a design-basis fuel cycle.

Figure 3. 8 Pressure boundary condition applied to the inner wall of PRZ, HL, RPV, HL and CL side of SG with magnified view during a) start b) end of a design-basis fuel cycle.

Figure 3. 9 Grid-load-Following power fluctuation profile (based on EDF data [10], that was used for generating the input wall temperature for HL and CL.

Figure 3. 10 Wall temperature of PRZ, HL, RPV or CL side of SG under grid-load-following power operation (with heat-up and cool-down conditions maintained similar as the design-basis loading cycle).

3.4 Example Heat Transfer Analysis Results Under Design-Basis Loading Cycle

Transient heat transfer analysis of the overall assembly was performed under design-basis loading cycle. Figure 3.11 shows the corresponding simulated temperature at all the 29740 elements of the SL and its HL and PRZ side nozzles. Figures 3.12 and 3.13 show the magnified version of Figure 3.11 during heat-up and cool-down, respectively. Whereas Figure 3.14 shows the FE simulated temperature at all the 7225 elements of the HL and its RPV and SG side nozzles assembly under design-basis loading. Figures 3.15 and 3.16 show the magnified version of Figure 3.14 during heat-up and cool-down, respectively. Figure 3.17 shows the temperature contour of entire assembly at different time of design-basis-loading. From Figures 3.11 to 3.13 the SL experience significant thermal stratification during heat-up and cool-down. Whereas, from Figures 3.14 to 3.16 the HL doesn't experience much thermal stratification during heat-up and cool-down as compared to the SL. Although thermal stratification in a component is dependent on applied thermal boundary conditions, it is typical that thermal stratification happens mostly in a component with slow moving fluid between two differential heat sources. This is particularly in case of SL in which the flow rate is typically low, and the flow is between lower-temperature HL (with assumed maximum temperature of 326.4 °C, refer Table 3.1) and higher-temperature HL (with assumed maximum temperature of 347.3 °C, refer Table 3.1). Nevertheless, significant differential nodal/elemental temperature (both along the length and thickness) can lead to significant stress and plastic deformation (depending on the connected system mechanical boundary conditions). The related stress analysis results are discussed in next section.

Figure 3.11 FE simulated temperature at all the 29740 elements of the SL and its HL and PRZ side nozzles assembly under design-basis loading (Note, individual color represents the time-series temperature of different elements).

Figure 3.12 Magnified figure of Figure 13 showing the FE simulated temperature at all the 29740 elements during heat-up.

Figure 3. 13 Magnified figure of Figure 3.11 showing the FE simulated temperature at all the 29740 elements during cool-down.

Figure 3. 14 FE simulated temperature at all the 7225 elements of the HL and its RPV and SG side nozzles assembly under design-basis loading (Note, individual color represents the time-series temperature of different elements).

Figure 3. 15 Magnified figure of Figure 16 showing the FE simulated temperature at all the 7225 elements during heat-up.

Figure 3. 16 Magnified figure of Figure 16 showing the FE simulated temperature at all the 7225 elements during cool-down.

Figure 3. 17 Temperature (unit: °C) contour of entire assembly at different time of design-basis-loading.

3.5 Example Heat Transfer Analysis Results Under EDF-Grid-Load-following Loading Cycle

Transient heat transfer analysis of the overall assembly was also performed under EDF-grid-load-following loading cycle. Figure 3.18 shows the corresponding FE simulated temperature at all the 29740 elements of the SL and its HL and PRZ side nozzles assembly. Whereas Figure 3.19 shows the magnified version of Figure 3.18 showing nodal temperature fluctuations during grid-load-following full-power-operation. Similarly, 3.20 shows the simulated temperature at all the 7225 elements of the HL and its RPV and SG end nozzles assembly. Whereas Figure 3.21 shows the magnified version of Figure 3.20 showing nodal temperature fluctuations of HL during grid-load-following power-operation. These types of results were used for validating the AI/ML based temperature prediction model (discussed in section 5), which can be used in an online monitoring or digital-twin system without conducting a FE based heat transfer analysis for each and every real-time input process measurement.

Figure 3. 18 FE simulated temperature at all the 29740 elements of the SL and its HL and PRZ side nozzles assembly under grid-load-following loading (Note, individual color represents the time-series temperature of different elements).

Figure 3. 19 Magnified figure of Figure 3.18 showing the FE simulated temperatures at all the 29740 elements during grid-load-following power-operation.

Figure 3. 20 FE simulated temperature at all the 7225 elements of the HL and its RPV and SG side nozzles assembly under grid-load-following loading (Note, individual color represents the time-series temperature of different elements).

Figure 3. 21 Magnified figure of Figure 3.20 showing the FE simulated temperature at all the 7225 elements during grid-load-following power-operation.

4 System level Thermal-Mechanical Stress Analysis Under Design-Basis Loading

In this section, we discuss a finite element (FE) based system level thermal-mechanical stress analysis model to simulate spatial-temporal stress/strain states under a design-basis (DB) loading cycle. The stress-analysis model was built based on the base FE model discussed in section 3. The finite elements of the base model were appropriately changed from 3D-hexahedral heat transfer elements to 3D-hexahedral structural elements. Using the resulting model, the thermal-mechanical stress analysis was performed under combined primary-loop internal pressure transient (refer Fig. 3.8) and all the transient nodal temperature from the previous heat transfer analysis conducted under the DB loading cycle. The system-level model was restrained in all directions at bottom-head of RPV, SG and PRZ. This is in assumptions that all these components are welded to a skirt support at their bottom-head and the bottom part of the skirt are bolted to the ground or supporting pedestal. The restraining boundary conditions for an actual reactor can substantially vary and can be different from plant to plant. Nevertheless, the aim of discussed work is to develop a methodology for a system level digital-twin model development, identify stress hotspots and quantify stress/strain states based on which fatigue testing activities can be prioritized. The details of the material property used, and the stress analysis results are discussed below.

4.1 Material Properties Used

The stress analysis model was developed using the temperature dependent mechanical properties such as expansion coefficients, elastic modulus, yield stress and kinematic hardening properties. These properties were earlier estimated based on the ANL conducted tensile tests funded through the LWRS program. Tables 4.1 to 4.6 show the related mechanical properties were used for the mentioned stress analysis model. Note that all the yield and hardening parameters are based on 0.05% offset-strain than the conventional 0.2% offset-strain yield limit. This is to better capture the plasticity region of a component.

Table 4. 1 Expansion coefficients for 316SS and 508LAS base, 316SS-SW filler, and 316SS-508LAS DW filler and butter welds

Temp (°C)	316 SS	508 LAS	SW- E316-16 filler weld	DW-In 82 Filler weld	DW-In 182 butter weld
	Expansion coeff (1 / °C)	Expansion coeff (1 / °C)	Expansion coeff (1 / °C)	Expansion coeff (1 / °C)	Expansion coeff (1 / °C)
21.11	2.84E-06	8.0805e-06	4.4273e-07	3.3078e-06	7.9477e-06
31.11	2.84E-06	8.2561e-06	4.4273e-07	4.067e-06	7.8772e-06
41.11	3.47E-06	8.7299e-06	8.7463e-07	4.7487e-06	7.8772e-06
51.11	4.64E-06	9.1746e-06	2.2e-06	5.2931e-06	7.8772e-06
61.11	5.72E-06	9.5914e-06	3.4306e-06	5.7206e-06	7.8772e-06
71.11	6.74E-06	9.9815e-06	4.5703e-06	6.0495e-06	8.8574e-06
81.11	7.68E-06	1.0346e-05	5.6232e-06	6.2969e-06	9.9318e-06
91.11	8.55E-06	1.0686e-05	6.5934e-06	6.4781e-06	1.0949e-05
101.11	9.35E-06	1.1003e-05	7.4849e-06	6.6072e-06	1.1855e-05

111.11	1.01E-05	1.1298e-05	8.3017e-06	6.6965e-06	1.2624e-05
121.11	1.08E-05	1.1572e-05	9.0479e-06	6.7574e-06	1.3251e-05
131.11	1.14E-05	1.1826e-05	9.7275e-06	6.7998e-06	1.375e-05
141.11	1.20E-05	1.2062e-05	1.0344e-05	6.8322e-06	1.414e-05
151.11	1.25E-05	1.2281e-05	1.0903e-05	6.8621e-06	1.4445e-05
161.11	1.30E-05	1.2483e-05	1.1407e-05	6.896e-06	1.4693e-05
171.11	1.34E-05	1.267e-05	1.186e-05	6.9392e-06	1.4906e-05
181.11	1.38E-05	1.2843e-05	1.2267e-05	6.9961e-06	1.5104e-05
191.11	1.41E-05	1.3004e-05	1.2632e-05	7.0699e-06	1.5301e-05
201.11	1.44E-05	1.3153e-05	1.2958e-05	7.1633e-06	1.5506e-05
211.11	1.47E-05	1.3292e-05	1.325e-05	7.278e-06	1.572e-05
221.11	1.49E-05	1.3422e-05	1.3512e-05	7.415e-06	1.5941e-05
231.11	1.52E-05	1.3544e-05	1.3747e-05	7.5745e-06	1.6162e-05
241.11	1.53E-05	1.3659e-05	1.396e-05	7.7563e-06	1.6372e-05
251.11	1.55E-05	1.3768e-05	1.4155e-05	7.9594e-06	1.6558e-05
261.11	1.56E-05	1.3873e-05	1.4336e-05	8.1823e-06	1.6709e-05
271.11	1.58E-05	1.3974e-05	1.4506e-05	8.4232e-06	1.6816e-05
281.11	1.59E-05	1.4073e-05	1.4671e-05	8.6799e-06	1.6872e-05
291.11	1.60E-05	1.4172e-05	1.4833e-05	8.9497e-06	1.6878e-05
301.11	1.61E-05	1.427e-05	1.4998e-05	9.2298e-06	1.6842e-05
311.11	1.62E-05	1.437e-05	1.5168e-05	9.5171e-06	1.6783e-05
321.11	1.63E-05	1.4473e-05	1.5348e-05	9.8083e-06	1.6728e-05
331.11	1.64E-05	1.4579e-05	1.5543e-05	1.01e-05	1.672e-05
341.11	1.65E-05	1.469e-05	1.5755e-05	1.0389e-05	1.6811e-05
350	1.65E-05	1.4794e-05	1.5963e-05	1.0642e-05	1.7028e-05

Table 4. 2 Tensile elastic-plastic properties used for 316SS base metal

Tensile test no.	Temperature (°C)	Elastic modulus (GPa)	Poisson ratio	0.05% offset-strain yield stress (MPa)	Kinematic hardening parameter C1 (MPa)	Kinematic hardening parameter γ
T02	22	175.1	0.27	217.41	13942	128.24
T04	300	157.92	0.27	145.03	4373.5	33.25

Table 4. 3 Tensile elastic-plastic properties used for 316SS SMW-Filler Weld and 316SS Cladding

Tensile test no.	Temperature (°C)	Elastic modulus (GPa)	Poisson ratio	0.05% offset-strain yield stress (MPa)	Kinematic hardening parameter C1 (MPa)	Kinematic hardening parameter γ
T03	22	131.98	0.27	414.56	5901.8	65.922
T05	300	129.11	0.27	345.8	4285.5	41.449

Table 4. 4 Tensile elastic-plastic properties used for 508 LAS base metal

Tensile test no.	Temperature (°C)	Elastic modulus (GPa)	Poisson ratio	0.05% offset-strain yield stress (MPa)	Kinematic hardening parameter C1 (MPa)	Kinematic hardening parameter γ
T06	22	209.72	0.27	494.36	2861.4	0
T10	300	194.01	0.27	406.63	12240	57.768

Table 4. 5 Tensile elastic-plastic properties used for DMW-Butter weld

Tensile test no.	Temperature (°C)	Elastic modulus (GPa)	Poisson ratio	0.05% offset-strain yield stress (MPa)	Kinematic hardening parameter C1 (MPa)	Kinematic hardening parameter γ
T16	22	149.7	0.27	387.64	9964.5	90.498
T15	300	146.28	0.27	322	6307	64.861

Table 4. 6 Tensile elastic-plastic properties used for DMW-Filler weld

Tensile test no.	Temperature (°C)	Elastic modulus (GPa)	Poisson ratio	0.05% offset-strain yield stress (MPa)	Kinematic hardening parameter C1 (MPa)	Kinematic hardening parameter γ
T14	22	172.64	0.27	420.14	12023	99.532
T13	300	196.57	0.27	359.72	6556.5	56.92

4.2 Stress Analysis Results of RPV

The primary aim of a system level model was to simulate the realistic lateral (or in-plane) and vertical displacements that were transferred to the HL and SL pipes and their assemblies. Due to internal pressure and thermal expansion, the RPV expand both laterally and vertically leading to substantial bending force on the connected systems i.e., the HL. In turn the displacements of HL due to its own internal pressure and thermal expansion and the displacements carried away from RPV can transfer to the next connecting system i.e., the SL. Unless, a full system level model simulated, the true picture of stress/strain in HL and SL cannot be predicted and hence the life and failure mode of those components. Figures 4.1, 4.2 and 4.3 show the in-plane-X-axis in-plane-Y-axis, and out-plane-Z-axis displacements of RPV at a typical time during the full-power operation (at 432 days of the design-basis-loading cycle). Note that the HL is along the X-axis of the overall system (refer Figure 3.2) and the center of the overall model is laid at the center of the RPV (and at the bottom of the RPV). From Figure 4.1 both the in-plane-X and Y directions experience radially symmetric displacements despite only one side of the RCS loop is modeled. The in-plane-X direction experiences approximately 9 mm of displacement, whereas in-plane-Y direction experiences approximately 14 mm of displacement. The slightly higher displacement in Y direction could be due to complex multi-axial effect of thermal and displacement boundary conditions associated with a system level model. To note that in an actual 2-loop reactor there will be only two HLs that have to be placed symmetrically either in the X-Z or Y-Z plane. So, in an actual reactor, there can also be a differential displacement between in-plane-X and in-plane-Y

directions. Figure 4.3 shows the out-plane vertical displacement of RPV. This figure shows a maximum vertical displacement of 42.5 mm at top of the RPV. Whereas the HL-CL-nozzle region of RPV experiences approximately a vertical displacement of 31.2 mm. Combinedly the in-plane and out-plane displacements can create substantial bending to the next connected system i.e., in this case the HL. Figure 4.4 shows the max. principal stress of RPV at a typical time during the full-power operation (at 432 days of the design-basis-loading cycle) showing stress hotspots at the RPV supports (i.e., at the bottom head) and HL/CL nozzle regions. However, as mentioned before the magnitude of stress/strain and the location of hotspots can substantially vary and can be different from plant to plant depending on the thermal-mechanical boundary conditions of that plant. The discussed result is just one example.

Figure 4. 1 In-plane-X-axis displacement (U1) of RPV at a typical time during the full-power operation (at 432 days of the design-basis-loading cycle) with a) isometric view of full RPV, b) isometric view near HL & CL nozzles, and c) top view near HL & CL nozzles (Note the displacements are in meter).

Figure 4. 2 In-plane-Y-axis displacement (U2) of RPV at a typical time during the full-power operation (at 432 days of the design-basis-loading cycle) with a) isometric view of full RPV, b) isometric view near HL & CL nozzles, and c) top view near HL & CL nozzles (Note the displacements are in meter).

Figure 4. 3 Out-plane-Z-axis displacement (U3) of RPV at a typical time during the full-power operation (at 432 days of the design-basis-loading cycle) with the displacements are in meter.

Figure 4. 4 Max. principal stress of RPV at a typical time during the full-power operation (at 432 days of the design-basis-loading cycle) with a) isometric view of full RPV, b) isometric view near HL & CL nozzles (Note the stresses are in Pascal).

4.3 Stress Analysis Results of HL and it's RPV-side and SG-side DMW-SMW Nozzles

Stress analysis results of the HL pipe and its nozzle assembly analyzed to check if there is any stress/strain hotspots and plastic strain regions. For example, Figures 4.5, 4.6 and 4.7 show the various contour plots (of temperature, max. principal thermal strain, max. principal total strain, plastic strain magnitude, equivalent or mises stress, and max. principal stress) of RPV-side-nozzle, base HL pipe and the SG-side-nozzle of HL. These contour plots are at a typical time during the full-power operation (at 432 days of the design-basis-loading cycle). From these figures the multi-material nozzles experience varied thermal strain, whereas the 316SS base HL-pipe experiences uniform thermal strain. This is due to different material systems in nozzles and associated expansion coefficients. Similar is the reasons for the variation of other parameters in RPV-side and SG-side HL nozzles. From Figures 4.5d and 4.7d, both the nozzles experience plastic yielding in the regions of DMW, SMW and SS safe-side (refer Figures 3.3). Plastic yielding is more prominent in the SS safe end of both the nozzles. Also, the SS HL pipe shows significant plastic yielding at both the ends (those connect to the safe end of RPV-side and SG-side nozzles) and at the nozzle area of SL. Large plastic deformation can lead to accelerated corrosion and cracking in these regions. However, crack initiation will be dependent on the evolution of these plastic regions (e.g. cyclic hardening). This is associated with multiple fatigue cycles and its interaction with reactor coolant environment. Overall, due to the system-level thermal-mechanical boundary conditions, the HL pipe and nozzle assembly can experience substantial displacements. For example, Figure 4.8 shows the magnified (magnification factor =10) displacement contours of HL and its DMW-SMW nozzles at different time of the design-basis-loading cycle. The observed maximum displacement magnitude is approximately of 44.5 mm.

Figure 4. 5 Various contour plot of RPV-side nozzle of HL at a typical time during the full-power operation (at 432 days of the design-basis-loading cycle) with a) temperature (°C), b) max. principal thermal strain (m/m), c) max. principal total strain (m/m), d) plastic strain magnitude (m/m), e) equivalent or mises stress (Pa), and f) max. principal stress (Pa) contours.

Figure 4. 6 Various contour plot of HL 316SS base pipe at a typical time during the full-power operation (at 432 days of the design-basis-loading cycle) with a) temperature (°C), b) max. principal thermal strain (m/m), c) max. principal total strain (m/m), d) plastic strain magnitude (m/m), e) equivalent or mises stress (Pa), and f) max. principal stress (Pa) contours.

Figure 4. 7 Various contour plot of SG-side nozzle of HL at a typical time during the full-power operation (at 432 days of the design-basis-loading cycle) with a) temperature ($^{\circ}\text{C}$), b) max. principal thermal strain (m/m), c) max. principal total strain (m/m), d) plastic strain magnitude (m/m), e) equivalent or mises stress (Pa), and f) max. principal stress (Pa) contours.

Figure 4. 8 Magnified (magnification factor =10) displacement (m) contours of HL and its DMW-SMW nozzles at different time of design-basis-loading (Note: Mesh shows the undeformed shape).

4.4 Stress Analysis Results of SL and it's HL-side and PRZ-side DMW-SMW Nozzles

Stress analysis results of the SL pipe and its nozzle assembly are analyzed to check if there is any stress/strain hotspots and plastic strain regions. For example, Figures 4.9, 4.10 and 4.11 show the various contour plots (of temperature, max. principal thermal strain, max. principal total strain, plastic strain magnitude, equivalent or mises stress, and max. principal stress) of HL-side-nozzle, base-metal SL pipe and the PRZ-side-nozzle of SL, respectively. These contour plots are at a typical time during the full-power operation (at 432 days of the design-basis-loading cycle). Unlike HL pipes (for which both the nozzles show significant plastic yielding), only the HL-side nozzle of SL shows significant plastic yielding (refer Figure 4.9d). Similarly, unlike the SS-base HL pipe, the SS-base SL pipe doesn't experience much plastic yielding except near the HL-side nozzle. Figure 4.12 shows the magnified (magnification factor =10) displacement contours of SL and its DMW-SMW nozzles at different time of the design-basis-loading cycle. From this figure the observed maximum displacement magnitude is approximately of 74.12 mm. This is much higher displacement than that experienced by HL (44.5 mm). Despite the higher displacement, the SL experience less plastic yielding. Overall, the discrepancy is associated with the geometry of the individual components and the connected system thermal-mechanical displacement boundary conditions.

Figure 4. 9 Various contour plot of HL-side nozzle of SL at a typical time during the full-power operation (at 432 days of the design-basis-loading cycle) with a) temperature ($^{\circ}\text{C}$), b) max. principal thermal strain (m/m), c) max. principal total strain (m/m), d) plastic strain magnitude (m/m), e) equivalent or mises stress (Pa), and f) max. principal stress (Pa) contours.

Figure 4. 10 Various contour plot of SL 316SS base pipe at a typical time during the full-power operation (at 432 days of the design-basis-loading cycle) with a) temperature ($^{\circ}\text{C}$), b) max. principal thermal strain (m/m), c) max. principal total strain (m/m), d) plastic strain magnitude (m/m), e) equivalent or mises stress (Pa), and f) max. principal stress (Pa) contours.

Figure 4. 11 Various contour plot of PRZ-side nozzle of SL at a typical time during the full-power operation (at 432 days of the design-basis-loading cycle) with a) temperature ($^{\circ}\text{C}$), b) max. principal thermal strain (m/m), c) max. principal total strain (m/m), d) plastic strain magnitude (m/m), e) equivalent or mises stress (Pa), and f) max. principal stress (Pa) contours.

Figure 4. 12 Magnified (magnification factor =10) displacement (m) contours of SL and its DMW-SMW nozzles at different time of design-basis-loading (Note: Mesh shows the undeformed shape).

5 Recurrent Neural Network Based Multi-Time-Series Temperature Prediction at any Inside/Outside Thickness of a Component Under Thermal Stratification and 100+ Years of Different Loading Cycles

In this section, the implementation of an AI/ML based recurrent neural network (RNN) model is discussed. This is for multi-time series temperature prediction at random inside/outside thickness of a reactor component. Prediction of cyclic stress/strain states and the associated fatigue life of a component first requires the knowledge of spatial distribution of temperature at any given time. This includes the time-dependent temperature gradient both along the length and thickness of a component. The traditional way of predicting spatial-temporal variation of temperature is through FE model-based heat transfer analysis. Although, the FE based approach is a well-established approach for component temperature prediction, it has four major drawbacks: a) each change in input/process thermal boundary conditions requires to rerun the heat transfer analysis, b) simulating for longer duration (e.g. under multi-year-multi-cycle reactor loading) is not only computationally time consuming but issues of storing large amount of FE simulated result database, c) requires specific skill to perform heat transfer analysis, d) in general designed as an offline predictive tools, not suitable for online/real-time applications. These drawbacks can be a hinderance for implementing FE based digital-twin technology for real-time state prediction of reactor components. Note that for safe and economical operation of US nuclear fleet under long-term-operation (way beyond the design life of 40 years), it is necessary to adopt more digital technology such as digital-twin. With the rapid advancement of AI/ML based technology, real-time prediction of temperature and other structural state is possible. In the reported work we propose a RNN based model for predicting temperature of a reactor component at any given time and locations (including inside the thickness of a component). The developed model can be extended in future to predict the cyclic stress state of a component. The proposed multi-time-series prediction model validated against two laboratory experiment-based test cases with metal surface temperatures predicted at multiple locations. The related results are discussed in section 5.2 and 5.3, respectively. In addition, the model is also validated against the FE model results for predicting temperature at multiple locations in a typical cross-Section of an RPV-side-HL-Nozzle (refer section 5.4) and at multiple locations along-the-length of a SL-pipe-nozzle-assembly subjected to thermal stratification (refer section 5.5). The FE based validation models were tested both for design-basis (DB) and EDF (Électricité de France) data [10] based grid-load-following (EDF-GLF) loading cycle. The validated model then used for predicting temperature at the above-mentioned component locations for 100+ years of reactor operation subjected to combined DB, EDF-GLF and randomized grid-load-following (RANDOM-GLF) loading Cycles. The eventual aim is to extend the discussed AI/ML model for predicting the time-series stress and strains at any spatial locations of a reactor component subjected to long-term-operation and the above type loading cycles. Based on the stress/strain time-series, the remaining life of a component at any given time can be predicted in real-time, without requiring the help of any skilled analyst. The proposed AI/ML based expert elicitation system would only require the information of few input/process variables (e.g., time-dependent primary loop pressure, temperature, etc.) measured from few existing sensors, without the need of installing any additional sensor systems. Note that installing new sensors is a major constraint for rapid digitalization and implementation of AI/ML technologies in nuclear sector. This is not only due to highly regulated nuclear industry, but also due to inaccessible locations and high radiation environment for sensor placements. The details of the theoretical background and model results are discussed below.

5.1 Theoretical Background

Recurrent neural network is a class of artificial neural network. However, unlike a sequential neural network, RNN must remember all states (within a selected window). This is some sort of remembering the past memory or temporal dynamic behavior. Our hypothesis of using RNN for structural state prediction is based on the fundamental principles of fracture mechanics. For example, fatigue state perdition at a given time require the knowledge of previous strain hardened states and/or previous defect conditions. For example, according to Paris law of fracture mechanics the crack-growth rate at time ‘ t ’ can be expressed as:

$$\frac{da}{dt_t} = C\Delta K^m \quad (5.1)$$

where, C and m are the two material constants, and K is the geometry dependent stress-intensity-factor (SIF). The SIF depends on current state of stress field (σ_t), and function of previous state of crack length (a_{t-1}) and can be expressed as:

$$K = \sigma_t f(a_{t-1}) \quad (5.2)$$

From Eqs. (5.1) and (5.2), it can be found that the fatigue state at a current time is memory dependent and depend on the past state. Hence in our assumption, RNN based predictive model can be used for prediction of structural states. Figure 5.1 shows the schematic of a RNN for a single-input-single-output (SISO) structure with multi-step strides (or multi time-step memory). Assuming a SISO system, the predicted output $\hat{y}_t$ at a time t can be expressed as follows:

$$\hat{y}_t = W_y h_t + b_y \quad (5.3)$$

Where, the hidden state at time t can be expressed in terms of previous hidden state and current input x_t as:

$$h_t = \phi(W_x x_t + W_h h_{t-1}) + b_h \quad (5.4)$$

In Eq. (5.4) the hidden state at time $t - 1$ can be expressed as:

$$h_{t-1} = \phi(W_x x_{t-1} + W_h h_{t-2}) + b_h \quad (5.5)$$

Similarly, the hidden state at time $t - s - 1$ can be expressed as in Eq. (5.6) and so on.

$$h_{t-s-1} = \phi(W_x x_{t-s} + W_h h_{t-s}) + b_h \quad (5.6)$$

In Eqs. (5.3) to (5.6) ϕ is the activation function with each time-step hidden states are fed from the previous step hidden states and the input features at that time step (refer Figure 5.1). In the discussed model, Rectified Linear Unit (ReLU) and linear activation functions were used for all the hidden layers and output layer, respectively. In Eqs. (5.3) to (5.6), W_x, W_y, W_h are the weight parameters for input, output, and hidden state, respectively. Whereas b_y and b_h are the bias parameters for output and hidden state, respectively. These parameters must be estimated based on historical input versus output data and by optimizing a loss function such as mean-square-error-based loss function given as below:

$$L = \sum_{p=1}^{p=t} (y_p - \hat{y}_p)^2 \quad (5.7)$$

where, y_p and $\hat{y}_t$ are respectively the ground truth and predicted values of the output.

Figure 5. 1 Schematic of a RNN for a single-input-single-output structure with a) Basic structure with single-step stride (or single time-step memory), b) multi-step stride (or multi time-step memory).

Eqs (5.3) to (5.7) are the mathematical representation of a SISO network with a single hidden layer with single hidden state at a given time. The network structure for a MIMO system with multiple hidden layers with each layer with multiple hidden states can become immensely complex. Figure 5.2 shows the schematic of an example RNN for a MIMO system with multiple hidden layers, with each layer having different hidden states. The total number of parameters in the below example network can be found using the flowing expression:

$$N = N_{1-2} + N_{2-3} + N_{3-4} \quad (5.8)$$

Where, N_{1-2} , N_{2-3} and N_{3-4} are the no. of parameters for the networks from layer-1 to layer-2, layer-2 to layer-3, and layer-3 to layer-4 and can be expressed as:

$$N_{1-2} = [(h1 + i) \times h1] + h1 \quad (5.9)$$

$$N_{2-3} = [h1 \times h2] + h2 \quad (5.10)$$

$$N_{3-4} = [h2 \times o] + o \quad (5.11)$$

In Eqs. (5.9) to (5.11) h_1 and h_2 are the no. of hidden states in hidden layer-1 and 2, respectively. Whereas i and o are respectively the number of input feature time-series and output time-series. For example, in case of along-the-length-temperature prediction in SL-pipe-nozzle-assembly (refer section 5.5), with number of process inputs: $i = 3$ (coolant-water temperature measurements at the ID of HL, RPV and PRZ), number of output prediction: $o = 53$, number of states in hidden layer-1: $h1 = 256$ and hidden layer-2: $h2 = 256$, the total number of parameters to be optimized/trained are = 145,973. The keras based AI/ML library [11] was used for implementing the above mentioned RNN model.

Figure 5. 2 Schematic of a RNN for a multi-input-multi-output structure with multiple hidden layers, with each layer having different hidden states.

5.2 Case – 1: Experimental Validation with SISO-Model Based Prediction of Temperature in an In-air Fatigue Test Loop

First a single-input-single-output (SISO) model was developed to validate the RNN model against experimental data. The data from ET-F67 fatigue specimen (refer section 2.2) was used for the mentioned model. The ET-F67 specimen was a DMW joint specimen fatigue tested at in-air condition. Figure 5.3 shows the in-air test frame that was used for fatigue testing of the ET-F67 specimen. In general, before conducting the main fatigue test the specimen along with the pull rod heated from room temperature to the desired isothermal fatigue test temperature under a stress-free condition (while allowing free thermal expansion of the specimen). The heating process was done in multiple steps similar during in a real reactor heat-up process. For the regular fatigue testing, the specimen-pull-rod drivetrain (refer Figure 5.4) is heated up only once and after the main fatigue test finished (under the stated isothermal temperature and mechanical strain/stress cycles), the drivetrain is cooled down completing a single thermal cycle. However, for this test case of ET-F67, the drivetrain was heated up and cooled down in multiple cycles (in a stress-free condition), before conducting the main mechanical

fatigue test. The purpose of the above-mentioned thermal cycling was to collect temperature data very similar to the actual reactor thermal cycling (although in a stressed condition compared to the stress-free condition during ET-F67 thermal cycling). Multiple thermocouples (TC) were placed at different locations of the drivetrain (refer Figure 5.4). Out of the measurements from various TCs, the measurements of TC at top shoulder of the specimen were used for controlling the induction heater. The associated data was used as input/process data for the mentioned SISO based RNN model. The measurements from the TC at the center of the specimen were used as the output data of the RNN model. Similar model can be developed for predicting temperature at any random locations (output) of a component for given input or process measurements (e.g., the coolant temperature at the HL, RPV, PRZ, etc.). The component level temperature prediction results are discussed in sections 5.4 and 5.5. Nevertheless Figures 5.5 and 5.6, respectively show the time versus temperature measurements at the induction heater controlling TC and the TC at the specimen gage center. Out of the approximately 130 hours of thermal-cycling data, approximately first 20 hours of data were used for training the RNN model. As any data-driven based AI/ML model first it is required to train a model (basically to find the optimized model parameters), then the trained model can be used for predicting unknown outputs for a given new input features (e.g., the process measurements or field variables in a reactor). The mentioned SISO model once trained using the first 20 hours of input-output data, was then used for predicting the output (here the temperature at the center of the specimen) for a given process inputs (in this case induction heater controlling temperature). Figure 5.7 shows the probability distribution of the input and output data those were fed to the SISO-RNN model for training the model (for 0 hours to 20 hours). Whereas Figure 5.8 show the probability distribution of the input and output data those were fed to the SISO-RNN model for validation or testing of the model (for 20 hours to 130 hours). Figure 5.9 shows the iteration versus MSE values while training the SISO-RNN model. The outputs were predicted for both the training and test/validation case inputs or process measurements. Figure 5.10 shows the predicted versus actual output (here the temperature at the center of the specimen) for both training and test inputs. Figure 5.11 shows the magnified view of Figure 5.10 showing the predicted training portion of the data. Whereas Figure 5.12 shows the magnified view of Figure 5.10 showing the predicted test portion of the data. These figure shows the RNN model can accurately predict the temperature under very similar thermal cycles in an actual reactor.

Figure 5. 3 a) In-air fatigue test frame with induction heating coil b) LEPEL induction heating system c) Close view of induction heating coil and specimen.

Figure 5. 4 Location of thermocouples on a fatigue specimen which were spot welded to the specimen.

Figure 5. 5 Time versus temperature measurements at the induction heater controlling TC which was used as the process input of the SISO-RNN model.

Figure 5. 6 Time versus temperature measurements at the specimen gage center which was used as the output of the SISO-RNN model.

Figure 5. 7 Probability distribution of the input (x1) and output (y1) data those were fed to the SISO-RNN model for training the model.

Figure 5. 8 Probability distribution of the input (x1) and output (y1) data those were fed to the SISO-RNN model for validation or testing of the model.

Figure 5. 9 Iteration versus mean-square-error (MSE) values while training the SISO-RNN model.

Figure 5. 10 Predicted versus actual training and test data.

Figure 5. 11 Magnified view of Figure 10 showing the predicted training portion of the data.

Figure 5. 12 Magnified view of Figure 10 showing the predicted test portion of the data.

5.3 Case – 2: Experimental Validation with MIMO-Model Based Prediction of Temperature in a PWR-water Fatigue Test Loop

Similar as the SISO model (discussed in section 5.3), a Multi-Input-Multi-output (MIMO) model was constructed based on the experimental data. However, the MIMO model was to check how accurately the RNN model can predict the temperature at multiple locations given only a single set of parameters optimized in one go. The MIMO model validation was done using data from a PWR-water fatigue test loop. Figure 5.13 shows the mentioned PWR-water fatigue test frame at ANL. Whereas Figure 5.14 shows the LABVIEW screen shot showing the schematic of various component of the complex test loop, which is similar as an actual reactor but without any irradiated material. Unlike the in-air test, where the TCs can be directly instrumented to the specimen, in a PWR-water test loop the TCs are instrumented at the various locations of the autoclave, pull-rod and other locations of the test loop (refer Figures 5.14 and 5.15). Along with TCs, other type of sensors such as for measuring loop flow velocity, electro chemical potential (ECP), pressure, etc. were also used. Table 5.1 shows the summary of the input feature (process measurements) and output feature names those were used for training and validating the MIMO-RNN model. The training and test data were taken from an earlier fatigue test case EN-F20. The fatigue test was conducted using a 508LAS specimen subjected to PWR-primary-loop-coolant environment. Unlike in the SISO model case (for which multiple thermal cycles were conducted), for the MIMO model case the test was conducted under a single thermal cycle with initial heat-up to the desired isothermal test temperature, isothermal main fatigue test and then cool-down of the test loop after main fatigue test. The MIMO model was tested for two subcases:

- a) Experimental MIMO prediction case-a: With mixed temperature and other sensor measurements as input features.
- b) Experimental MIMO prediction case-b: considering the training model only with temperature measurements as process-input features.

Different sensor measurements were used as input features. For example, TC readings at heat exchanger outlet, preheater inlet and outlet (Figure 5.16) were considered as input features for both case-a and case-b models. Whereas, electro-chemical-potential sensor readings (Figure 5.17), flow-velocity (Figure 5.18), pressure sensor reading (Figure 5.19), and ambient temperature reading from a faulty TC (Figure 5.20) were used as additional input features only for case-a model. The ambient temperature TC was found faulty after analyzing the sensor data. The TC might have failed during the test. However, we deliberately included the measurements from this faulty sensor as one of the input feature or process variable. This is to check how accurately the model predict the output despite using the measurements from a faulty sensor. Note, a faulty sensor can automatically be identified based on various statistical measures and the related data can be isolated from building a model. However, inclusion of a faulty sensor was to check and show the importance of selecting appropriate input features for development of a more accurate model. Nevertheless, both the case-a and case-b models were trained and tested for same set of output measurements. Figure 5.21 shows output measurements (which are basically the TC readings at various locations of the autoclave and pull-rod) for both training and test data. Figure 5.22 shows the cross-correlation matrix of all (both training and test) input and output measurements. This figure shows that some of the input features (e.g., the non-temperature sensor measurements and faulty ambient temperature TC refer Table 5.1) are not well correlated with the output measurements. Hence

use of some of these input features can affect the overall accuracy of the prediction results (refer case-a prediction results). In an automated environment, based on these type cross-correlation matrix a particular input feature (or sensor readings) can be dropped or considered in the prediction model. Figure 5.22 shows the probability distribution of example input and output time-series. From this figure the probability distribution of input and output are not similar. However, the MIMO model would be able to predict the output temperature fair accurately. The prediction results are discussed below.

Figure 5. 13 PWR-water fatigue test loop.

Figure 5. 14 LABVIEW screen shot showing the schematic of various component of test loop.

Figure 5. 15 LABVIEW screen shot showing the location of heat zone, autoclave inlet and outlet and location of various thermocouples (TC) with respect to autoclave, pull rod and specimen.

Table 5. 1 Summary of the input feature (process measurement) and output feature names that were used for training and validating the MIMO-RNN model.

Input/output time series (or feature) serial no.	Input feature (process measurement) names	Output feature names	Axial distance of the TC locations from center of the specimen (gage- length)
1	Heat exchanger outlet TC		NA
2	Preheater inlet TC		NA
3	Preheater outlet TC		NA
4	Electrochemical potential (ECP) sensor		NA
5	Loop water flow sensor		NA
6	Loop water pressure sensor		NA
7	TC ambient		NA
8		TC +9 in (or TC-1)	+9 in
9		TC +4 in (or TC-2)	+4 in
10		TC +0.875 in (or TC-3)	+0.875 in
11		TC 0 in (or TC-4)	0 in
12		TC -0.875 in (or TC-5)	-0.875 in
13		TC -4 in (or TC-6)	-4 in
14		TC -9 in (or TC-7)	-9 in

Figure 5. 16 All (both training and test) input/process measurements: TC readings at heat exchanger outlet, preheater inlet and outlet.

Figure 5. 17 All (both training and test) input/process measurements: Loop electro-chemical-potential sensor readings.

Figure 5. 18 All (both training and test) input/process measurements: Loop flow-velocity sensor readings.

Figure 5. 19 All (both training and test) input/process measurements: Loop pressure sensor readings.

Figure 5. 20 All (both training and test) input/process measurements: Ambient temperature readings from a faulty TC.

Figure 5. 21 Output measurements (which are basically the TC readings at various locations of the autoclave) for both training and test data.

Figure 5. 22 Cross-correlation matrix of all (both training and test) input and output measurements.

Figure 5. 23 Probability distribution of example input and output time-series (considering both training and test data).

5.3.1 Experimental MIMO prediction case-a: considering the training model with both temperature and non-temperature measurements as process-input features

The case-a MIMO model was trained and tested with both temperature and non-temperature measurements as process-input features. Figure 5.24 shows the corresponding iteration versus MSE values during the training of the model. Figure 5.25 shows the prediction versus actual measurements at the central most TC in the autoclave (at ‘TC 0 in’ which is also cross-referenced as TC-4, refer Table 5.1). Figures 5.26 shows the AI/ML predicted output at all the TC locations along the autoclave and pull-rod. Whereas Figure 5.27 shows the corresponding actual TC readings. From Figures 5.25 to 5.27, there is a good comparison between predicted and actual measurements for most of the test duration except during end cooling-down steps. This is possibly due to the unnecessary input features that might have bias the model. These type of unnecessary input features (including the ambient temperature measurements from a faulty TC) can be automatically removed based on the cross-correlation matrix data (Figure 5.22).

Figure 5. 24 Experimental MIMO prediction case -a: Iteration versus mean-square-error (MSE) values during the training of the model.

Figure 5. 25 Experimental MIMO prediction case -a: Prediction versus actual measurements at the central most TC in the autoclave (at 'TC 0 in', which is also cross-referenced as TC-4).

Figure 5. 26 Experimental MIMO prediction case -a: Predicted output at all the TC locations along the autoclave and pull-rod.

Figure 5. 27 Experimental MIMO prediction case -a: Measured readings at all the TC locations along the autoclave and pull-rod.

5.3.2 Experimental MIMO prediction case-b: considering the training model only with temperature measurements as process-input features

To improve the model accuracy (compared to case-a model), the case-b MIMO model was trained and tested considering only three TC (at heat exchanger outlet, preheater inlet and outlet) measurements as process-input features. Figure 5.28 shows the corresponding iteration versus MSE values during the training of the model. Figure 5.29 shows the prediction versus actual measurements at the central most TC in the autoclave (at ‘TC 0 in’, which is also cross-referenced as TC-4). Comparing Figure 5.29 with Figure 5.25, it can be seen that the case-b model produces better accuracy than the case-a model. This can be further evident by comparing the Figure 5.30 (which shows the AI/ML predicted output at all the TC locations along the autoclave and pull-rod) with Figure 5.27 (which shows corresponding experimental measurements). Nevertheless, these type of results shows the importance of selecting proper process measurements as input features.

Figure 5. 28 Experimental MIMO prediction case -b: Iteration versus mean-square-error (MSE) values during the training of the model.

Figure 5. 29 Experimental MIMO prediction case -b: Prediction versus actual measurements at the central most TC in the autoclave (at ‘TC 0 in’, which is also cross-referenced as TC-4).

Figure 5. 30 Experimental MIMO prediction case -b: Predicted output at all the TC locations along the autoclave and pull-rod.

5.4 Case-3: MIMO-Model Based Inside-Thickness Temperature Prediction at a Cross-Section of RPV-side-HL-Nozzle

The above discussed experimentally validated MIMO model was further validated against FE model results both under design-basis (DB) and EDF based grid-load-following (EDF-GLF) loading cycle. This is for predicting temperature at multiple locations in a typical cross-Section of an RPV-side-HL-Nozzle, given only three input/process temperature measurements: Fluid temperature at the outlet of RPV (i.e., the HL temperature), inlet of RPV (i.e., the CL temperature or the temperature at the ID surface of RPV) and the temperature measured at the outlet of PRZ. We assume all these three temperatures can be available from plant existing instrumentation. Whereas the output time-series at any random locations (including inside thickness) of a component which cannot be measured (due to unavailability of sensors or unforeseeable reasons) can be predicted using the proposed MIMO-RNN model. However, the model needs to be first trained for a given set of historical data comprising of the same set of input and output sensors although not the same data. Note that, historical data from real sensors cannot be available if there are no physical sensors existing at those locations. In that case we propose to conduct a onetime heat transfer analysis for a single or part of a DB loading cycle and the resulting input-output data can be used as virtual sensor data for training the MIMO-RNN model.

In this section we discuss the temperature prediction results for an RPV-side-HL-Nozzle. This is for predicting temperature at multiple locations in a typical cross-Section of the RPV-side-HL-Nozzle. Figure 5.31 shows the highlighted FE element locations (both inside and thickness elements) at which the temperatures were predicted. Before any prediction, the FE based heat transfer analysis results for first half of a DB cycle (capturing both heat-up and full-power-operation conditions) were used for training the MIMO-RNN model. The trained model then used for predicting temperature at the above-mentioned component locations for 100+ years of reactor operation subjected to combined DB (only second half of DB cycle capturing both cool-down and portion of full-power-operation conditions), EDF-GLF and randomized grid-load-following (RANDOM-GLF) loading Cycles. Figures 5.32 to 5.35 show the related input-output data used for training the model. Figure 5.36 shows the associated iteration versus mean-square-error (MSE) values during the training of the model. Figures 5.37 to 5.40 show the various assumed input/process measurements for which the temperature time-series were predicted. Figures 5.41 to 5.47 show temperature prediction results at the highlighted element locations in Figure 5.31. Comparing the Figure 5.42 with Figure 5.43 and Figure 5.44 with Figure 5.45 the AI/ML model can predict temperature very similar as the FE model. These type results show the spatial-temporal temperature at any random locations (including inside the thickness) of a component can be predicted without requiring an FE model other than for the initial training data (for which a one time FE model required if input-output training data are not available from actual sensors). With this confidence the MIMO-RNN model was further used for predicting temperature for hundred RANDOM-GLF cycles. The related results are shown in Figures 5.41, 5.46 and 5.47.

Figure 5. 33 RPV-side-HL-Nozzle temperature prediction model: Magnified version of Figure 5.32 showing the training-input data only during the heat-up operation.

Figure 5. 34 RPV-side-HL-Nozzle temperature prediction model: Training output temperature (encapsulating only first-half of a DB cycle) at all the highlighted 100 elements of RPV-side-HL-Nozzle (each element represented by randomly generated colors showing the qualitative nature of the data).

Figure 5. 35 RPV-side-HL-Nozzle temperature prediction model: Magnified version of Figure 5.34 showing the training-output data only during the heat-up operation of the DB cycle.

Figure 5. 36 RPV-side-HL-Nozzle temperature prediction model: Iteration versus mean-square-error (MSE) values during the training of the model.

Figure 5. 37 RPV-side-HL-Nozzle temperature prediction model: Test case input/process temperature (encapsulating approximately 120 years of DB, EDF-GLF and RANDOM-GLF loading cycles).

Figure 5. 38 RPV-side-HL-Nozzle temperature prediction model: Magnified version of Figure 5.37 showing the test case inputs during second half of the DB cycle.

Figure 5. 39 RPV-side-HL-Nozzle temperature prediction model: Magnified version of Figure 5.37 showing the test case inputs during an EDF-GLF cycle.

Figure 5. 40 RPV-side-HL-Nozzle temperature prediction model: Magnified version of Figure 5.37 showing the test case inputs during a RANDOM-GLF cycle.

Figure 5. 41 RPV-side-HL-Nozzle temperature prediction model: AI/ML predicted temperature at all the highlighted 100 elements of RPV-side-HL-Nozzle for approximately 120 years (consisting of second half of a DB, one full EDF-GLF and hundred RANDOM-GLF loading cycles), This is with each element represented by randomly generated colors showing the qualitative nature of the data.

Figure 5. 42 RPV-side-HL-Nozzle temperature prediction model: Magnified version of Figure 5.41 showing the AI/ML temperature prediction during the second half of a DB cycle.

Figure 5. 43 RPV-side-HL-Nozzle temperature prediction model: Corresponding FE predicted temperature (at all the highlighted elements of RPV-side-HL-Nozzle) during the second half of a DB cycle.

Figure 5. 44 RPV-side-HL-Nozzle temperature prediction model: Magnified version of Figure 5.41 showing the temperature prediction during an EDF-GLF cycle.

Figure 5.45 RPV-side-HL-Nozzle temperature prediction model: Corresponding FE predicted temperature (at all the highlighted elements of RPV-side-HL-Nozzle) during the EDF-GLF cycle.

Figure 5.46 RPV-side-HL-Nozzle temperature prediction model: Magnified version of Figure 5.41 showing the temperature prediction during a RANDOM-GLF cycle.

Figure 5. 47 RPV-side-HL-Nozzle temperature prediction model: Magnified version of Figure 5.46 showing the temperature fluctuations during the full-power-operation of the RANDOM-GLF cycle.

5.5 Case-4: MIMO-Model Based Temperature Prediction Along-the-length of SL-pipe-nozzle-assembly Subjected to Thermal Stratification

In addition to the above-discussed FE model case of temperature prediction at a cross-section of the RPV-side-HL-Nozzle, the MIMO-RNN model was also tested for temperature prediction along-the-length of a SL-pipe-nozzle-assembly subjected to thermal stratification. Figure 5.48 shows the highlighted FE element locations (along the OD length of a SL-pipe-nozzle-assembly) at which the temperatures were predicted. Similar as the case-3, first the model was trained using input-output data from the FE based heat transfer analysis results. The model was trained for the same set of assumed input/process measurements as the case-3 model. This is because of the assumption that the process measurements represent the bulk behavior of coolant water and are only measured at few locations and would not change much from location to location. That means the training input for case-3 model (shown in Figures 5.32 and 5.33) remain same for the training input of case-4 model. Similarly, the test/validation case input/process measurements for case-3 model (shown in Figures 5.37 to 5.40) remain same for the training input for case-4 model. However, both the location dependent output measurements change and must be measured (from real sensor) or predicted. Similar as case-3, before any prediction, the FE based heat transfer analysis results for first half of a DB cycle (capturing both heat-up and full-power-operation conditions) were used to train the MIMO-RNN model. The trained model then used for predicting temperature at the above-mentioned component locations for 100+ years of reactor operation subjected to combined DB (only second half of DB cycle capturing both cool-down and portion of full-power-operation conditions), EDF-GLF and randomized grid-load-following (RANDOM-GLF) loading Cycles. Figures 5.49 and to 5.50 show the related FE model-based output

data used for training the model. Figure 5.51 shows the associated iteration versus MSE values during the training of the model. Figures 5.52 to 5.58 show temperature prediction results at the highlighted element locations in Figure 5.48. Comparing the Figure 5.53 with Figure 5.54 and Figure 5.55 with Figure 5.56, the AI/ML model can predict temperature very similar as the FE model and under complex thermal stratification conditions. These type results show the spatial-temporal temperature at any random locations (subjected to complex thermal stratification) of a component can be predicted without requiring an FE model other than for the initial training data. With this confidence the MIMO-RNN model was also used for predicting temperature along-the-length of the SL-pipe-nozzle-assembly for hundred RANDOM-GLF cycles. The related results are shown in Figures 5.52, 5.57 and 5.58. Note that, the purpose of this exercise is to demonstrate a methodology and the capability of the discussed MIMO-RNN model. The actual results will be dependent on the plant specific input/process measurements, geometry of the actual component and thermal-mechanical boundary conditions.

Figure 5. 48 SL-pipe-nozzle-assembly temperature prediction model: Highlighted 53 FE element locations (along the OD length of SL-pipe-nozzle-assembly) at which the temperatures were predicted.

Figure 5. 49 SL-pipe-nozzle-assembly temperature prediction model: Training output temperature (encapsulating only first-half of a DB cycle) at all the highlighted 53 elements of SL-pipe-nozzle-assembly (each element represented by randomly generated colors showing the qualitative nature of the data).

Figure 5. 50 SL-pipe-nozzle-assembly temperature prediction model: Magnified version of Figure 5.49 showing the training-output data only during the heat-up operation of the DB cycle.

Figure 5. 51 SL-pipe-nozzle-assembly temperature prediction model: Iteration versus mean-square-error (MSE) values during the training of the model.

Figure 5. 52 SL-pipe-nozzle-assembly temperature prediction model: AI/ML predicted temperature at all the highlighted 53 elements of SL-pipe-nozzle-assembly for approximately 120 years (consisting of second half of a DB, one full EDF-GLF and hundred RANDOM-GLF loading cycles), This is with each element represented by randomly generated colors showing the qualitative nature of the data.

Figure 5. 53 SL-pipe-nozzle-assembly temperature prediction model: Magnified version of Figure 5. 52 showing the AI/ML temperature prediction during the second half of a DB cycle.

Figure 5. 54 SL-pipe-nozzle-assembly temperature prediction model: Corresponding FE predicted temperature (at all the highlighted elements of SL-pipe-nozzle-assembly) during the second half of a DB cycle.

Figure 5. 55 SL-pipe-nozzle-assembly temperature prediction model: Magnified version of Figure 5. 52 showing the temperature prediction during an EDF-GLF cycle.

Figure 5. 56 SL-pipe-nozzle-assembly temperature prediction model: Corresponding FE predicted temperature (at all the highlighted elements of SL-pipe-nozzle-assembly) during the EDF-GLF cycle.

Figure 5. 57 SL-pipe-nozzle-assembly temperature prediction model: Magnified version of Figure 5. 52 showing the temperature prediction during a RANDOM-GLF cycle.

Figure 5. 58 SL-pipe-nozzle-assembly temperature prediction model: Magnified version of Figure 5. 52 showing the temperature fluctuations during the full-power-operation of the RANDOM-GLF cycle.

6 Major Conclusion and Suggested Future Studies

The major conclusions and suggested future studies are as follows:

6.1 Major Conclusions

- 1) Fatigue test data from testing of different Nickel alloy based DMW specimens (both for 82/182 and 52/152 based welds and both for solid-weld and joint-weld representing the actual reactor multi-metal nozzles) are presented. The resulting fatigue lives were compared to the NUREG-6909 based best-fit and design fatigue curves. From the comparison of 82/182 and 52/152 DMW test data with NUREG-6909 best-fit curve, most of the reported test data fall way away from the NUREG-6909 suggested best-fit or mean curve. The NUREG-6909 suggested best-fit curve is the best-fit curve of austenitic stainless steel and due to lack of enough data on Nickel-based welds, this is currently being used for predicting the life of Nickel-alloy-based welded components. However, the above observation may require higher scaling factor (e.g., ASME suggested factor of 20 on cycles rather than the current NUREG-6909 suggested factor of 12 on cycles) for scaling the austenitic-stainless-steel best-fit-curve for estimating the design or safe-life of a welded component. Accordingly for example, if a DMW component experience a strain amplitude of 0.6% the PWR-water life of the component would be 52 cycles instead of 85 cycles. The design life can be further reduced for higher strain amplitude and if intermittent lower-amplitude cycles are considered. More fatigue tests of the joint specimens (both under in-air and coolant-water conditions) are required to further characterize the fatigue behavior of welded components. In addition, effect of the mean-strain (actual reactor component are in general subjected to stain cycles with substantial mean strain), intermittent small-amplitude cycles and strain rate need to be assessed.
- 2) A system level CAD and finite element model was developed which consists of reactor pressure vessel, part of steam generator, part of pressurizer, hot leg, and surge line. This is with detailed nozzle geometry and thermal-mechanical material properties of different metals to simulate realistic thermal-mechanical stress under connected system global thermal-mechanical boundary conditions. Based on this system level model different transient heat transfer analyses were performed considering thermal boundary condition under design-basis and EDF (Électricité de France) data-based grid-load-following loading cycles. The resulting data were used in subsequent system level thermal-mechanical stress analysis and for generating spatial-temporal training and validation data for the development of a system level digital-twin model.
- 3) A system level thermal-mechanical stress analysis was performed under design-basis loading cycle and connected system thermal-mechanical boundary conditions and thermal stratification in surge line pipe. The system level model can help identifying the damage-prone hotspots. From the simulation results it is found that the hot leg and the surge line nozzle that connect to the hot leg can experience significant stress and strain and could be one of the weakest links in the overall reactor coolant system. Without a system level model simulation or system level experiments or through actual plant component failure, identifying the realistic structural hotspots and estimating

the related stress/strain is not possible. We suggest using similar approach for more accurately estimating the stress-strain states and resulting fatigue life of a component.

- 4) A ready-to-use AI/ML based DT model is developed for multi-time-series temperature prediction at any inside/outside thickness locations of PWR pressure boundary components. This is by using Recurrent-neural-network (RNN) and keras machine learning libraries. The RNN based DT model was well validated against laboratory test-based and FE model-based data sets. The expert-elicitation DT model framework was developed assuming field/input/process measurements can be available from a few existing plant sensors and can readily be used by NPP operators.

6.2 Suggested Future Studies

- 1) Additional tests of DMW and base metals subjected to more realistic stress-strain profiles such as predicted through the above-mentioned system-level model.
- 2) Extension of the above-mentioned DT model for spatial-temporal stress-strain prediction of reactor components subjected to multi cycle loadings.
- 3) Component or system level fatigue testing (as also suggested by Electric Power Research Institute as one of the major gaps in fatigue evaluation) and/or simulation based predictive models for uncertainty reduction in fatigue life estimation.

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