One-Step Ahead Prediction of Thermal Mixing Tee Sensors with Long Short Term Memory (LSTM) Neural Networks

Maintenance of Advanced Reactor Sensors and Components

Nuclear Science and Engineering Division

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prepared by

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Abstract

High-temperature advanced reactors under development, such as sodium fast reactors (SFR) and molten salt cooled reactors (MSCR), are expected to offer lower levelized cost of energy (LCOE) compared to existing light water reactor (LWR's). In the existing light water reactors (LWR's), operation and maintenance (O&M) expenses constitute the largest fraction of the total operating cost. Some of the O&M costs are related maintenance of sensors which can fail due to exposure to harsh environment in a reactor. The O&M costs of Advanced Reactor (AR)'s are expected to constitute a significant fraction of the total cost as well, because of high temperature and radiation level in AR are likely to cause material fatigue and premature failure of sensors and components. The O&M costs in AR's could be reduced through integration of advanced informatics of performance-related sensors into a *digital twin* designed for reactor monitoring. For example, machine learning (ML) could be employed for real-time validation and correction of performance-related sensors, and reducing the number of performance-related physical sensor units through virtual sensing. As part of the effort, we investigate real-time validation of thermal hydraulic sensors through one-step ahead forecasting of sensor values using long short-term memory (LSTM) recurrent neural networks (RNN). The sensors are installed in a flow loop containing a thermal mixing tee, which is a common experimental model to study thermal fatigue in a thermal hydraulic loop. In addition, nonlinear transients generated in a thermal mixing tee constitute a good challenge data set for training and validation of ML algorithms. Sensors in this study include thermocouples, flow meters, and optical fibers for distributed temperature sensing. In one experiment, measurement data sets were obtained for a loop was filled with water, and in another experiment, measurements were performed on a loop filled with liquid metal Galinstan. We have also conducted preliminary investigation of one-step ahead prediction of fiber optics-based distributed temperature sensing with LSTM networks. In predicting fiber-based temperature measurements, we treated each gauge pitch of the fiber as an independent sensor. Accuracy of one-step ahead forecasting was estimated by calculating root mean square error (RMSE) for the test segment of time series of each sensor. RMSE's for temperature sensors in water loop were, for the most part, lower than for the same sensors in Galinstan loop. The RMSE's for flow meters were similar for both loops. The RMSE's for distributed temperature measured with the fiber optic sensor were similar to those of the point sensors. Results of this study demonstrated the capability of LSTM one-step ahead forecasting with RMSE comparable to uncertainty in sensor measurements.

1. Introduction

Nuclear energy currently provides the largest fraction of carbon-free electricity generation. Sustainability of nuclear energy requires it to be economically competitive with other forms of electricity generation, particularly those based on fossil fuels. High-temperature advanced reactors under development, such sodium fast reactors (SFR) and molten salt cooled reactors (MSCR) are expected to offer lower levelized cost of energy (LCOE) compared to existing light water reactor (LWR's). In the existing light water reactors (LWR's), operation and maintenance (O&M) expenses constitute the largest fraction of the total operating cost [1]. Some of the O&M costs are related maintenance of sensors which can fail due to exposure to harsh environment in a reactor. The O&M costs of Advanced Reactor (AR)'s are expected to constitute a significant fraction of the total cost as well, because of high temperature and radiation level in AR are likely to cause material fatigue and premature failure of sensors and components. The O&M costs in AR's could be reduced through integration of advanced informatics of performance-related sensors in into a *digital twin* designed for reactor monitoring. For example, machine learning (ML) could be employed for real-time validation and correction of performance-related sensors, and reducing the number of performance-related physical sensor units through virtual sensing [2]. As part of the effort, we investigate real-time validation of thermal hydraulic sensors through one-step ahead forecasting of sensor values using long short-term memory (LSTM) recurrent neural networks (RNN) [3,4]. The sensors are installed in a flow loop containing a thermal mixing tee, which is a common experimental model to study thermal fatigue in a thermal hydraulic loop [5-7]. In addition, nonlinear transients generated in a thermal mixing tee constitute a good challenge data set for training and validation of ML algorithms. Sensors in this study include thermocouples, flow meters, and optical fibers for distributed temperature sensing. In one experiment, measurement data sets were obtained for a loop was filled with water, and in another experiment, measurements were performed on a loop filled with liquid metal Galinstan. LSTM networks are trained on time series of each sensor, and then used to predict one-step ahead reading of each corresponding sensor. We have also conducted preliminary investigation of LSTM networks one-step ahead prediction of fiber optics-based distributed temperature sensing [7-10]. In predicting fiber-based temperature measurements, we treated each gauge pitch of the fiber as an independent sensor. Accuracy of one-step ahead forecasting was estimated by calculating root mean square error (RMSE) for the test segment of time series of each sensor. LSTM RNN was developed with MATLAB Deep Learning Toolbox. The LSTM networks we developed demonstrated the capability of one-step sensor measurement forecasting with errors comparable to uncertainty in sensor measurements.

2. Flow Loop with Thermal Mixing Tee

A flow loop with a thermal mixing tee was assembled and instrumented in prior work [5,6]. The P&ID (piping and instrumentation diagram) of the loop is shown in Figure 1. The loop was constructed with polycarbonate pipe sections. In one set of experiments, the loop was filled with water, and in another separate set of tests the loop was filled with liquid metal Galinstan. The fluids were maintained at ambient pressure. Fluid in the loop was circulated clockwise against gravity with a variable speed 1.5HP stainless circulation pump. A split in the main loop created “hot leg” and “cold leg” flows. Fluid pumped through the ‘hot leg’ was heated with a variable power Watlow FLC-16 heater, with maximum power rating of 4 kW_e. Fluid in the “hot leg” was eventually mixed with the “cold leg” fluid in a thermal tee, which is colored in red in Figure 1. The inner diameters of the “hot leg” and “cold leg” pipes were 0.75in and 1.5in, respectively. After mixing, fluid in the main loop was brought back to room temperature with a 130,000 BTU Shell & Tube standard heat exchanger, which was coupled to 11,300 BTU/hr chiller. Flow rate and temperature data were sampled using sensors at different points throughout the loop. Select sensors investigated in this report are shown in Figure 1. Temperatures of the “hot leg,” “cold leg,” and downstream of the thermal mixing tee were measured with thermocouples T_{hot} , T_{cold} , and T_{mix} . As shown in Figure 1, the thermocouples T_{hot} , T_{cold} , and T_{mix} were located 14.75in, 5.5in and 17.75in, respectively, from the thermal mixing tee. Mass flow rate in the “cold leg” and main loop was measured with two volumetric flow meters Q_{cold} and Q_{total} . Two fiber optic cables enclosed in narrow metallic thimbles were inserted into the hot and cold legs to measure distributed temperature in the thermal mixing tee.

Data was collected in separate experiments with water and liquid metal Galinstan fluids in the loop. Data was collected in separate experiments with water and liquid metal Galinstan fluids in the loop. Data was sampled by both the point sensors and the fiber every second. Data collection from point sensors was performed with LabVITM program, and fiber optic data was recorded with Luna Optical Distributed Sensor Interrogator (ODiSI) interface.

For reference, thermophysical properties at normal atmospheric pressure and room temperature of water and Galinstan (Ga 68.5%, In 21.5%, Sn 10%) fluids are listed in Table 1. Thermal diffusivity given as $\alpha=k/\rho c$, where k is thermal conductivity, c is specific heat capacity, and ρ is density. Thermal diffusivity is a measure of thermal inertia. Note that thermal diffusivity of Galinstan is an order of magnitude higher than that of water.

Table 1 – Fluid thermophysical properties of water and Galinstan at normal atmospheric pressure and room temperature

Fluid	ρ (kg/m ³)	c (J/kg*K)	k (W/m*K)	α (mm ² /s)
Water	1000	4183	0.5948	0.1422
Galinstan	6440	296	16.5	8.656

Figure 1 – Schematics of flow loop containing thermal mixing tee. Locations of measurements temperatures T_{hot} , T_{cold} , and T_{mix} , and flow rates Q_{cold} and Q_{total} are indicated in the diagram.

3. Flow Loop Transient Data

Transient temperature and flow rate data was collected in separate experiments with water and liquid metal Galinstan fluids in the loop. Temperature and flow rate transients were generated by varying heater power and pump speed, respectively, from within LabVIEW™ interface. Data was sampled by both the point sensors and fiber optic distributed temperature sensor every second. The temperature was measured using type K thermocouples, which are commonly found in nuclear applications because of relative radiation hardness. Maximum continuous temperature measurement with type K thermocouple is around 1,100°C. Accuracy of measurements with type K thermocouple is $\pm 1.1^\circ\text{C}$ or 0.4% (whichever is larger). The flow was measured using Turbine Blancett B110-500-1/2 flowmeters, which operate at temperatures up to 177°C. Accuracy of measurements is $\pm 1.0\%$ of reading, and repeatability is $\pm 0.1\%$.

2.1. Water loop

Figures 2 shows the time series of temperature $T_{\text{mix}} (^\circ\text{C})$ in water for approximately 3100s with one-second sampling rate.

Figure 2 – Time series of $T_{\text{mix}}(^\circ\text{C})$ in water sampled every second.

Time series of water temperatures $T_{\text{hot}}(^\circ\text{C})$ and $T_{\text{cold}}(^\circ\text{C})$, sampled every second, are displayed in Figure 3. Comparing Figures 2 and 3, one can observe that T_{mix} and T_{hot} are correlated.

Figure 3 – Time series of $T_{\text{hot}}(^\circ\text{C})$ and $T_{\text{cold}}(^\circ\text{C})$ in water sampled every second.

Time series of water flow rates Q_{cold} (L/s) and Q_{total} (L/s) sampled every second are displayed in Figure 4. The flow in the “hot leg” can be calculated as the $Q_{\text{total}} - Q_{\text{cold}}$. Comparing transient behavior of Q_{cold} and Q_{total} , one can observe that the two variables are highly correlated.

Figure 4 – Time series of flow rates Q_{cold} (L/s) and Q_{total} (L/s) in water loop sampled every second.

Note that for $t < 1000$ s, T_{mix} contains high-frequency noise, which could be appearing due to thermal striping in the thermal mixing tee. For $t > 2000$ s, both T_{mix} and T_{hot} time series exhibit high-frequency noise. This occurs when the values of Q_{cold} and Q_{total} are at the lowest levels during the observations. The noise in T_{hot} could be attributed to temperature fluctuations cause by the 4kW heater for the low levels of Q_{hot} , i.e., fluid flow in the hot leg.

2.1. Galinstan loop

Time series of T_{mix} (°C) in Galinstan, recorded for approximately 1900s with one-second sampling rate are shown in Figure 5. The time series contain high-frequency noise in the approximate region $300\text{s} < t < 1800\text{s}$, which could be attributed to thermal striping in the tee.

Figure 5 – Time series of T_{mix} temperature in Galinstan loop sampled every second.

Time series of T_{hot} (°C) and T_{cold} (°C) in Galinstan sampled every second are displayed in Figure 6. Unlike the temperatures for water, T_{mix} and T_{hot} for Galinstan are not as closely correlated.

Figure 6 – Time series of temperatures T_{hot} (°C) and T_{cold} (°C) in Galinstan loop sampled every second.

Time series of Q_{cold} (L/s) and Q_{total} (L/s) in Galinstan sampled every second are displayed in Figure 7. Similar to the case of water flow rate transients, Q_{cold} and Q_{total} in Galinstan are highly correlated.

Figure 7 – Time series of flow rates Q_{cold} (L/s) and Q_{total} (L/s) in Galinstan loop sampled every second.

4. One-Step Ahead Prediction of Thermal Mixing Tee Sensors with LSTM Networks in Water Loop

Using data collected in the flow loop, we developed one-step predictions of the sensors using long short term memory (LSTM) recurrent neural network (RNN). These LSTM networks contain ‘feedback loops’ within their structure, which make them “ideal” for predicting the long term evolution of dynamic systems, such as temperature or flow rate fluctuation. All neural networks were created using the MATLAB Deep Learning Toolbox. We partitioned the data from each sensor as follows: assigned the first 80% of the data for LSTM training, the subsequent 10% for validation, and the final 10% for testing/prediction with the model. Performance of LSTM network for each sensor was estimated by calculating root mean square error (RMSE) over the observation segment. For all simulations, we determined that best performance of LSTM network was obtained for number of hidden nodes equal to 80.

4.1. Temperature one-step ahead prediction

Figure 8(a) visualizes partitioning of the T_{mix} time series into LSTM training (blue), validation (yellow) and forecast (green) data segments. Zoomed-in test segment of T_{mix} time series is visualized in Figure 8(b). Data shown consists of the observed (colored red) and one-step ahead predicted (colored green) time series. For this segment, $RMSE = 0.025626^{\circ}C$, which is two orders of magnitude smaller than the Type K thermocouple measurement uncertainty of approximately $1^{\circ}C$. Note that the amplitude of fluctuations in the test segment is less than $1^{\circ}C$. The training data contains a segment with high frequency noise in the region $t < 1000s$, which can potentially explain low error in prediction of the test segment containing noise.

Figure 8 – (a) Partitioning of T_{mix} time series in water into training (blue), validation (yellow) and test (green) segments. The test segment is chosen to be as the last 10% of the time series. **(b)** Zoom-in of testing segment of T_{mix} showing observed (red) and one-step ahead predicted (green) values. $RMSE = 0.025626^{\circ}C$.

To determine that there was no data bias in LSTM network prediction, we have shifted the test segment to be approximately in the middle of T_{mix} time series. This is visualized in Figure 9(a). Note that the validation segment in Figure 9 is the test segment of Figure 8. Zoomed-in test segment with observed and predicted values colored in red and green, respectively, is displayed in Figure 9(b). For this location of test segment, $RMSE = 0.0628^{\circ}C$. The error is three times larger than the one for the test segment in Figure 8. However, the RMSE is still substantially smaller than the uncertainty in measurements. Note that the largest error in prediction in Figure 9 is near the “top hat” shaped region of the time series, which has an amplitude of approximately $2^{\circ}C$. The error in that region has the appearance of a DC offset of approximately $0.1^{\circ}C$.

Figure 9 – (a) Partitioning of T_{mix} time series into time series in water into training (blue), validation (yellow) and test (green) segments. The test segment is chosen to be approximately in the middle of the time series. **(b)** Zoom-in of testing segment of T_{mix} showing observed (red) and one-step ahead predicted (green) values. The location of the test segment is taken approximately from the middle of the T_{mix} time series. $RMSE = 0.0628^{\circ}C$.

Performance of LSTM network in one-step ahead prediction of T_{hot} is shown in Figure 10. Similar to data partitioning shown in Figure 8, the test segment in Figure 10(a) is chosen to be the last 10% of T_{hot} time series. Zoomed-in test segment of T_{hot} time series is visualized in Figure 10(b). Data shown consists of the observed (colored red) and one-step ahead predicted (colored green) time series. For this segment, $RMSE = 0.2358^{\circ}C$. This value is an order of magnitude larger than $RMSE$ for T_{mix} , but still significantly smaller than thermocouple measurement uncertainty. The reason for larger error could be attributed to larger amplitude (about $2^{\circ}C$) of T_{hot} fluctuations. One can observe that predicted values typically fall short of actual values for high-frequency fluctuations. Note that the training and validation data for LSTM network prediction of T_{hot} contains high-frequency noise.

Figure 10 – (a) Partitioning of T_{hot} time series in water into training (blue), validation (yellow) and test (green) segments. The test segment is chosen to be as the last 10% of the time series. **(b)** Zoom-in of testing segment of T_{hot} showing observed (red) and one-step ahead predicted (green) values.

For comparison, performance of LSTM network in one-step ahead prediction of T_{cold} is shown in Figure 11. Similar to data partitioning shown in Figure 8, the test segment in Figure 11(a) is chosen to be the last 10% of T_{cold} time series. Note that T_{cold} time series do not contain any high frequency noise. Zoomed-in test segment of T_{cold} time series is visualized in Figure 11(b). Data shown consists of the observed (colored red) and one-step ahead predicted (colored green) time series. For this segment, $RMSE = 0.0071^{\circ}C$. This error is an order of magnitude smaller than that obtained for one-step prediction of T_{mix} . The small error could be attributed to absence of high-frequency noise in T_{cold} time series.

(a)

(b)

Figure 11 – (a) Partitioning of T_{cold} time series in water into training (blue), validation (yellow) and test (green) segments. The test segment is chosen to be as the last 10% of the time series. (b) Zoom-in of testing segment of T_{mix} showing observed (red) and one-step ahead predicted (green) values. RMSE = 0.0071°C .

4.2. Flow rate one-step ahead prediction

Performance of LSTM network in one-step ahead prediction of Q_{cold} flow rate is shown in Figure 12. The test segment in Figure 12(a) is chosen to be approximately in the middle of Q_{cold} time series. Zoomed-in test segment of Q_{cold} time series is visualized in Figure 12(b). Data shown consists of the observed (colored red) and one-step ahead predicted (colored green) time series. The average value of Q_{cold} over the test segment is approximately 1L/s, so that the uncertainty in measurements is on the order of 0.01L/s. For one-step prediction with LSTM network, RMSE = 0.1612 L/s, which is an order of magnitude larger than the measurement uncertainty. Note the prediction error is particularly large near the sharp transitions, and has visual appearance similarity with Gibbs overshoot in harmonic representation of square pulses.

Figure 12 – (a) Partitioning of Q_{cold} time series in water into training (blue), validation (yellow) and test (green) segments. The test segment is chosen to be approximately in the middle of the time series. **(b)** Zoom-in of test segment of Q_{cold} showing observed (red) and one-step ahead predicted (green) values. RMSE = 0.1612 L/s.

Figure 13(a) shows partitioning of time series of total flow in water Q_{total} . The test segment is chosen to be the last 10% of the data set. Unlike the test segment of Q_{cold} , the test segment of Q_{total} time series does not contain rapid amplitude variations. Figure 13(b) shows zoomed-in test segment of Q_{total} with observed and predicted time series. For the test segment, RMSE = 0.061749 L/s. The average Q_{total} is approximately 2.4 L/s, so that the uncertainty in measurements is approximately 0.024 L/s. The RMSE in one-step ahead predictions is approximately three times larger than the measurement uncertainty. One can observe in Figure 13(b) that flow measurement contains high-frequency noise. One-step ahead prediction with LSTM network follows the general trend, but does not accurately forecast the amplitude of high-frequency fluctuations.

(a)

(b)

Figure 13 – (a) Partitioning of Q_{total} time series in water into training (blue), validation (yellow) and test (green) segments. The test segment is chosen to be the last 10% of the time series of Q_{total} . **(b)** Zoom-in of testing segment of Q_{total} showing observed (red) and one-step ahead predicted (green) values. RMSE = 0.061749 L/s.

5. One-Step Ahead Prediction of Thermal Mixing Tee Sensors with LSTM Networks in Galinstan Loop

Using data collected in the Galinstan flow loop, we developed one-step predictions of the sensors using LSTM networks. All neural networks were created using the MATLAB Deep Learning Toolbox. We partitioned the data from each sensor as follows: assigned the first 80% of the data for LSTM training, the subsequent 10% for validation, and the final 10% for testing/prediction with the model. Performance of LSTM network for each sensor was estimated by calculating RMSE over the test segment. For all simulations, we determined that best performance of LSTM network was obtained for number of hidden nodes equal to 80.

5.1. Temperature one-step ahead prediction

Figure 14(a) visualizes partitioning of the T_{mix} time series into LSTM training (blue), validation (yellow) and test (green) data segments. Zoomed-in test segment of T_{mix} time series is visualized in Figure 14(b). Data shown consists of the observed (red) and one-step ahead predicted (green) time series. For this segment, $\text{RMSE} = 0.2044\text{ }^{\circ}\text{C}$, which is an order of magnitude smaller than the Type K thermocouple measurement uncertainty of approximately 1°C . Note that RMSE for T_{mix} prediction in Galinstan is an order of magnitude larger than the RMSE for T_{mix} prediction in water.

Figure 14 – (a) Partitioning of T_{mix} time series in Galinstan into training (blue), validation (yellow) and test (green) segments. The test segment is chosen to be the last 10% of T_{mix} time series. **(b)** Zoom-in of test segment of T_{mix} in Galinstan showing observed (red) and one-step ahead (green) predicted values. RMSE = 0.2044 $^{\circ}\text{C}$.

To determine if RMSE depends on any properties of the test segment, we have selected the test segment to be approximately in the middle of T_{mix} time series. The new partitioning is shown in Figure 15(a). Zoomed-in test segment with observed (red) and predicted (green) time series is shown in Figure 15(b). This time RMSE = 0.2947 $^{\circ}\text{C}$, which is slightly larger than the RMSE calculated for the test segment in Figure 14(b). As can be seen from both Figures 15(a) and 15(b), the largest prediction error is for the very first value of the data point of the test segment. In general, LSTM prediction follows the mean of the time series but does not predict the actual values, particularly when there are rapid fluctuations.

(a)

(b)

Figure 15 – Partitioning of T_{mix} time series in Galinstan into training (blue), validation (yellow) and test (green) segments. The test segment is chosen to be approximately in the middle of T_{mix} time series. Zoom-in of test segment of T_{mix} in Galinstan showing observed (red) and one-step ahead predicted (green) values. RMSE = 0.2947 °C.

Prediction of T_{hot} in Galinstan is investigated in Figure 16(a), which shows partitioning of the time series into training (blue), validation (yellow), and test (green) segments. Zoomed-in test segment of T_{hot} in Galinstan is shown in Figure 16(b). For the test segment, RMSE = 0.2024 °C, which is smaller than the uncertainty in measurements. RMSE of T_{hot} is comparable to RMSE of T_{mix} . This is to be expected since fluctuations in T_{hot} introduced by the 4kW heater are translated into fluctuations of T_{mix} due to high thermal diffusivity of Galinstan. As with T_{mix} , RMSE of T_{hot} in Galinstan is larger than RMSE of T_{hot} in water.

(a)

(b)

Figure 16 – (a) Partitioning of T_{hot} time series in Galinstan into training (blue), validation (yellow) and test (green) segments. The test segment is chosen to be the last 10% of T_{hot} time series. **(b)** Zoom-in of test segment of T_{hot} showing observed (red) and one-step ahead predicted (green) values. RMSE = 0.2024 °C.

Partitioning of T_{cold} time series in Galinstan is shown in Figure 17(a). The test segment is chosen to be the last 10% of the time series. Zoomed-in test segment of T_{cold} is shown in Figure 17(b). For this segment, RMSE = 0.0526 °C, which is an order of magnitude smaller than RMSE of T_{hot} and T_{mix} . This is to be expected since the test segment of T_{cold} does not contain high frequency fluctuations. Note that the value of RMSE for T_{cold} in Galinstan is an order of magnitude lower than RMSE of T_{cold} in water.

(a)

(b)

Figure 17 – (a) Partitioning of T_{cold} time series in Galinstan into training (blue), validation (yellow) and test (green) segments. The test segment is chosen to be the last 10% of T_{cold} time series. **(b)** Zoom-in of test segment of T_{cold} showing observed (red) and one-step ahead predicted (green) values. RMSE = 0.0526 °C

5.2. Flow rate one-step ahead prediction

Partitioning of Q_{cold} time series into training (blue), validation (yellow), and test (green) regions is shown in Figure 18(a). Zoomed-in test segment of Q_{cold} is shown in Figure 18(b). The average value of Q_{cold} over the test segment is approximately 10L/s, giving the average uncertainty in measurements of 0.1L/s. For the test segment, RMSE = 0.1359 L/s. This value is comparable to the uncertainty in flow measurements. The RMSE of Q_{cold} in Galinstan and water have comparable values. Note that as in the case of Q_{cold} in water, the largest error in prediction of Q_{cold} in Galinstan occurs at the sharp transition.

Figure 18 – (a) Partitioning of Q_{cold} time series in Galinstan into training (blue), validation (yellow) and test (green) segments. The test segment is chosen to be the last 10% of Q_{cold} time series. (b) Zoom-in of test segment of Q_{cold} showing observed (red) and one-step ahead predicted (green) values. RMSE = 0.1359 L/s.

Partitioning of Q_{total} time series into training, validation, and test segments is shown in Figure 19(a). The test segment is chosen to be the last 10% of Q_{total} time series. Zoomed-in test segment of Q_{total} is shown in Figure 19(b). As in the case of Q_{cold} , the average uncertainty in measurements over the test segment is 0.1L/s. For the test segment, RMSE = 0.10546 L/s. This value is comparable to the uncertainty of flow measurements. As in the case of Q_{cold} , RMSE in Galinstan

is larger than RMSE in water loop. Note that for Galinstan loop, RMSE of Q_{total} is smaller than RMSE of Q_{cold} . This is consistent with the relationship between RMSE's of flow rates in water loop.

(a)

(b)

Figure 19 – (a) Partitioning of Q_{total} time series in Galinstan into training (blue), validation (yellow) and test (green) segments. The test segment is chosen to be the last 10% of Q_{cold} time series. **(b)** Zoom-in of test segment of Q_{total} showing observed (red) and one-step ahead predicted (green) values. RMSE = 0.10546 L/s.

6. One-Step Ahead Prediction of a Fiber-Optic Distributed Temperature Sensing in Water Loop

Two single mode fiber optic cables with their cladding removed were inserted into narrow stainless steel metallic thimbles, which were placed in the “hot” and “cold” legs of the thermal mixing tee. The fibers in the “cold leg” and “hot leg” are 5.2m and 3.64m long. The two fibers overlapped within the mixing zone as shown in Figure 20. Fiber readout consists of a 1550nm telecommunication wavelength laser continuously measures Rayleigh backscattering within the length of the fiber from sub-wavelength size intrinsic defects. The principle of distributed temperature measurements with the fiber optic sensors consists of thermal expansion of the fiber, which changes the pattern of Rayleigh scattering [7-10].

In this work, the fiber optic data was recorded with Luna Optical Distributed Sensor Interrogator (ODiSI 6000) interface, which relates changes in Rayleigh scattering to thermal strain, which can then be converted to fluid temperature values. The temperatures were measured relative to a laboratory reference standard of 22.8 °C. Temperature data measured with a fiber consists of a 2D matrix, where one dimension is the length of the fiber, and another dimension is time. Each segment of the fiber is treated as an independent sensor. Temperature was sampled every 0.05s for a total of 728s, and spatial resolution of measurements along the fiber length (gage pitch) was 2.6mm. Measurement uncertainty for ODiSI is 0.9°C.

Figure 20 – Schematics of Rayleigh scattering fiber-optic distributed temperature sensor installation in the thermal mixing tee.

Following the approach used for one-step ahead prediction of point sensors, we developed LSTM networks to forecast the temperature field measured by the fibers. In this preliminary work, we study forecasting of temperature measured with 7.5cm-long section of the fiber located at beginning of the in the “hot leg” and well before the thermal mixing tee. Each gauge pitch segment of the fiber was treated as an independent sensor. LSTM network was constructed for each gauge pitch, using 703s as training data and 25s as the test.

Results of the LSTM network test for the test segment chosen to be between times 225s and 250s are shown Figure 21. Measured temperature differential is displayed as pseudo-color 2D map in Figure 21(a). Warmer colors indicate higher temperature, as shown by the color bar. LSTM one-step ahead predictions are displayed in Figure 21(b). The RMSE averaged over all gauge pitch segments is 0.0445 °C. This error is smaller than the measurement uncertainty, and also smaller than RMSE for T_{hot} in water.

(a)

(b)

Figure 21 – (a) Measured temperature. (b) One-step ahead predicted temperature with LSTM network. RMSE averaged over all gauge pitches is 0.0445°C.

Figure 22 shows the results of LSTM one-step ahead prediction when the test segment is moved to a temporal location between 125s and 150s. The measured data is displayed as pseudo-color map in Figure 22(a). One-step ahead predictions are displayed as pseudo-color map in Figure 22(b). RMSE averaged over all gauge pitches is 0.2881°C , which is an order of magnitude higher compared to the RMSE of the test segment in Figure 21. However, the RMSE of Figure 22 is still smaller than the measurement uncertainty, and has value comparable to the RMSE of T_{hot} in water.

Figure 22 – (a) Measured temperature. (b) One-step ahead predicted temperature with LSTM network. RMSE averaged over all gauge pitches in the test segment is 0.2881°C .

7. Conclusions

We have investigated the strategies for reducing advanced reactor O&M costs through integration of advanced informatics of performance-related sensors into a digital twin designed for reactor monitoring. In particular, machine learning (ML) could be employed for real-time validation and correction of performance-related sensors, and reducing the number of performance-related physical sensor units through virtual sensing. As part of the effort, we investigate real-time validation of thermal hydraulic sensors through one-step ahead forecasting of sensor values using long short term memory (LSTM) recurrent neural networks (RNN). The sensors are installed in a flow loop containing a thermal mixing tee, which is a common experimental model to study thermal fatigue in a thermal hydraulic loop. In addition, nonlinear transients generated in a thermal mixing tee constitute a good challenge data set for training and validation of ML algorithms. Sensors in this study include thermocouples, flow meters, and optical fibers for distributed temperature sensing. In one experiment, measurement data sets were obtained for a loop was filled with water, and in another experiment measurements were performed on a loop filled with liquid metal Galinstan. We have also conducted preliminary investigation of one-step ahead prediction of fiber optics-based distributed temperature sensing with LSTM networks. In predicting fiber-based temperature measurements, we treated each gauge pitch of the fiber as an independent sensor. Accuracy of one-step ahead forecasting was estimated by calculating root mean square error (RMSE) for the test segment of time series of each sensor.

A summary of RMSE values of one-step ahead prediction with LSTM networks for each point sensor in water and Galinstan loops given in Tables 2 and 3, respectively. RMSE values for one-step prediction of distributed temperature sensing with fiber optic sensor in water loop are given in Table 4. RMSE's are calculated for each fiber gauge pitch segment and averaged over the length of the fiber segment.

Table 2 – RMSE for one-step prediction of sensor values in water loop

Variable	RMSE
T_{mix}	0.0303 °C
T_{mix} (middle)	0.0628 °C
T_{hot}	0.2358 °C
T_{cold}	0.0071 °C
Q_{cold}	0.1612 L/s
Q_{total}	0.061749 L/s

Table 3 – RMSE for one-step prediction of sensor values in Galinstan loop

Variable	RMSE
T_{mix}	0.2044 °C
T_{mix} (middle)	0.2947 °C
T_{hot}	0.2024 °C
T_{cold}	0.0526 °C
Q_{cold}	0.1359 L/s
Q_{total}	0.10546 L/s

Table 4 – RMSE values for one-step ahead prediction of distributed temperature sensing with fiber optic sensor in water loop. RMSE's are calculated for each fiber gauge pitch segment and averaged over the length of the fiber segment.

Variable	RMSE
$T_{\text{hot}} - 1$	0.0445°C
$T_{\text{hot}} - 2$	0.2881°C

RMSE's for temperature sensors in water loop were, for the most part, lower than for the same sensors in Galinstan loop. The RMSE's for flow meters were similar for both loops. The RMSE's for distributed temperature measured with the fiber optic sensor were similar to those of the point sensors. Results of this study demonstrated the capability of LSTM one-step ahead forecasting with RMSE comparable to uncertainty in sensor measurements.

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