Mitigation of Radiation-Induced Fiber Bragg Grating (FBG) Sensor Drifts in Intense Radiation Environments Based on Long-short-Term Memory (LSTM) Network

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ABSTRACT This paper reports in-pile testing results of radiation-resistant fiber Bragg grating (FBG) sensors at high temperatures, intense neutron irradiation environments, and machine learning methods for radiation-induced sensor drift mitigation and reactor anomaly identification. The in-pile testing of fiber sensors was carried out in an MIT test reactor for 180 days at a nominal operational temperature of 640°C and high neutron flux. The test results show that FBG sensors inscribed by a femtosecond laser in random airline pure silica fiber can withstand harsh environments in the reactor core but exhibit significant radiation-induced drifts. Machine learning algorithms based on long short-term memory (LSTM) networks have been used to detect reactor anomaly events and mitigate sensor drifts over a duration of up to 85 days. Through progressive supervised learning, the LSTM neural network can achieve FBG wavelength-to-temperature mapping within ±0.95°C, ±2.63°C and ±6.49°C with over 80.2%, 90%, and 95% levels of accuracy confidence, respectively. The LSTM can also identify reactor anomaly samples with an accuracy of over 94%. The results presented in this paper show that despite sensor drifts and anomaly interruptions, the LSTM-based method can effectively elucidate data harnessed by fiber sensors. Machine learning algorithms have the potential to improve situational awareness and control for a wide range of harsh environment applications, including nuclear power generation.

INDEX TERMS Fiber Bragg grating (FBG), Long Short-Term Memory (LSTM) network, radiation effects, reactor anomaly identification, supervised learning, sensor drifts mitigation, temperature measurement, wavelength-shift.

I. INTRODUCTION

Fiber optical sensors have been extensively utilized as versatile and highly multiplexable sensing devices to perform a wide array of measurements [1]. A unique feature of fiber optical sensors is their capability to perform high spatial resolution measurements using multiplexable devices such as fiber Bragg gratings (FBGs) or through various optical scattering processes [2,3]. Well-known for their resilience to survive harsh environments, fiber optical sensors can function in environments while other sensors fail. Large datasets harnessed by fiber sensors in harsh environments can significantly improve the safety and efficiency of various energy production processes using renewable, fossil, and nuclear fuels. However, like all other sensors intended for harsh environment applications, the performance and characteristics of fiber sensors could be influenced by the environment and incur significant drifts [4-7].

The deployment of fiber sensors in nuclear reactor cores to perform continuous and high spatial resolution measurements...
is of great interest to both civilian and military operators of nuclear energy systems. One of the most comprehensive studies of FBG sensors in harsh nuclear core environments was conducted by Fernandez and Gusarov et al., who reported the use of FBGs endured gamma radiation doses up to 160MGy and neutron fluence up to 1.47×10^{17} fast neutrons per square centimeter for temperature monitoring with 3°C accuracy [7-10]. In 2016, Remy et al. reported the radiation-induced compaction (RIC) effect on FBG sensors exposed to 2.83×10^{19} fast neutrons per square centimeter with a 4°C accuracy in temperature [5]. In 2017, a number of in-pile tests were performed at the MIT test reactor (MTR) to evaluate the radiation resilience of fiber Bragg grating (FBG) sensors exposed to extremely high neutron flux (>2×10^{14} fast neutrons per second per square centimeter) at a nominal operational temperature of 640°C for an entire testing period of 180 days [2]. These encouraging results suggest that fiber sensors have the potential to perform high spatial resolution monitoring to improve the safety and operational efficiency of nuclear energy systems.

However, the test results show that continuous neutron irradiation exerted on FBG sensors produces drifts of fiber sensor characteristics with complex drift patterns. The overall trend of the FBG wavelength drift is approximately linear to the accumulated neutron flux, but the drift rate varies over different testing periods [2]. The continuous evolution of sensor characteristics and interruptions by simulated anomalies poses significant challenges in delineating the sensor response. In this paper, we report a machine learning approach based on a long short-term memory (LSTM) neural network [18] to mitigate sensor drifts induced by harsh neutron and gamma irradiation and identify reactor anomaly events. LSTM is a special type of Recurrent Neural Network (RNN), which is commonly used in processing sequence data with temporal dependencies. Compared to RNN, LSTM has the advantage of handling long-term information based on the gate mechanism [19-21]. Modeling the long-term radiation-induced effects, including fiber compaction, can be a challenge, but LSTM can directly model the drifting data of the Bragg wavelength and learn the hidden dependencies over long testing periods. The radiation resistance of our fiber sensor makes it possible for reliable long-term learning over the entire testing period. The results presented in this paper show that the continuous data harness and training of the LSTM neural network can effectively mitigate the adverse effects of sensor drifts, leading to accurate temperature measurements and anomaly event identification.

II. EXPERIMENTS AND DEFINITIONS

Two optical fibers, pure-silica random airline (RAL) fibers and F-doped cladding single-mode fibers, were considered based on previous literature studies and the cost of fibers for potential large-scale deployment [2]. When exposed to accumulated gamma dose of 1 MGy, F-doped single-mode fibers exhibited lower radiation-induced attenuation (RIA), but larger temperature measurement error (~2.3°C) compared to pure silica core (PSC) fibers (~0.7°C) [4]. Pure silica core (PSC) fibers, which exhibit radiation-induced loss on the order of a few dB per kilometer in the infrared, are known to be one of the most radiation-resistant fibers in terms of low RIA [14]. With identical thermal expansion coefficients and similar responses under neutron or gamma radiation in both the fiber core and cladding regions, the pure-silica RAL fiber has conceivable radiation resistance, and it can also be manufactured at a much lower cost [15] compared to other pure-silica fibers such as photonic crystal fibers [11]. In this case, we selected pure silica RAL fibers.

The pure-silica RAL fiber used in this study was nano-engineered using the outside vapor deposition (OVD) process [12,13]. The FBG sensor was inscribed by a femtosecond laser through a phase-mask approach in a pure-silica random airline fiber. Details of the random airline fiber and FBG fabrication procedure can be found in [2]. Fig. 1 provides a general description of the experiment. The fiber was inserted into a stainless tube and lowered to the reactor core (PSC), which endured a few dB per kilometer in the infrared, to be exposed to simulated irradiation. The reactor power and temperature over 180 days are shown in Fig. 1a. The average fast neutron flux of the reactor where the fiber sensor was located was approximately 2.1×10^{14} fast neutrons per second per square centimeter. The fast neutrons are neutrons with an average kinetic energy of >0.1 MeV.
reflection spectra of the FBG were interrogated using a tunable laser (TUNICS T100S-HP) from 1510 nm to 1580 nm and acquired every 20 s continuously with a wavelength resolution of 2 pm [2]. This yield approximately $7.8 \times 10^5$ frames of spectra over 180 days. The temperature of the Ti holder in the reactor core was monitored using four thermocouples [2]. The FBG response with accumulated fluences over different testing periods is shown in Fig. 1b. It is clear that both the FBG peak wavelength and the reflected amplitude underwent significant drift.

Fig. 1c and d show the reactor power profile, temperature measured by thermocouples, FBG peak wavelength, and corresponding amplitude over 180 days. The reactor was maintained at 625℃-645℃ during normal operation at approximately 5.7 MW, while simulated anomaly events were instigated, which led to sharp fluctuations in the reactor power and temperature, as shown in Fig. 1c. Four reactor states are defined to identify reactor events: Normal-Operation (NO), Anomaly Rising (AR), Anomaly Falling (AF), and Anomaly-Duration (AD).

The NO state is defined when the reactor power remains constant at approximately 5.7 MW with a temperature around 625℃-645℃. Significant drifts of the FBG peak wavelength induced by harsh neutron and gamma irradiation can be observed in Fig. 1d (day 40-50 for example).

Anomaly-Rising (AR) and Anomaly Falling (AF) states are defined when simulated anomaly events lead to sharp fluctuations in neutron power and temperature (day 55 and day 81, for example). For quantification, we chose 20℃ as an empirical threshold, given that the measured temperature varied between 625℃-645℃ during normal operations. Periods between ARs or AFs are defined as Anomaly-Duration (AD). Thus, we have the following definitions:

$$s = \begin{cases} 
\text{NO} & 625℃ \leq T \leq 645℃ \text{ and } |\Delta T| \leq 20℃ \\
\text{AF} & \Delta T < -20℃ \\
\text{AR} & \Delta T > 20℃ \\
\text{AD} & \text{otherwise}, 
\end{cases}$$

(1)

where $|\Delta T|$ is the temperature variation within a short period of time $\Delta t$, which will be discussed in the next section.

III. DRIFT MITIGATION SYSTEM DESIGN

Temperature and cumulative radiation are two key factors that influence FBG wavelength variations, as shown in Fig. 1c. To distinguish between temperature and radiation effects, the following relationship is defined: In a period of time $\Delta t$, the Bragg wavelength shift (BWS) $\Delta \lambda_B$, owing to variations in temperature $\Delta T$ and cumulative radiation effect $C_R\Delta t$, is given by

$$\frac{\Delta \lambda_B}{\lambda_B} = C_T \Delta T + C_R\Delta t,$$

(2)

where $C_T$ is the coefficient of temperature variation and $C_R$ is the coefficient of radiation-induced effects over a period of time. The factor $\Delta t$ is defined as the period of time from an arbitrary past time $t_0$ to the current time $t$ ($t_0 < t$) because we can only use samples from the past in real-world applications, and $\Delta T$ is defined as the temperature variation from $t_0$ to $t$.

Our task was to map from Bragg wavelength to the current temperature, distinguishing radiation-induced BWS. The testing periods under different reactor states provide good opportunities to distinguish $C_T\Delta T$ and $C_R\Delta t$. The temperature variations are nearly 0 in a single “NO” testing period, so if $\Delta t$ is large enough for accumulation of radiation-induced effects, we can safely set $C_T\Delta T$ to 0. As for “AF” or “AR” periods, the temperature and wavelength vary a lot within a short period of time, so if $\Delta t$ is small enough to satisfy $|C_R\Delta t| << |C_T\Delta T|$, we can also set $C_R\Delta t$ to 0 and estimate the other coefficient.

However, the continuous evolution of sensor characteristics will finally result in the evolution of these two coefficients over the entire testing period, and the coefficients calculated from one testing period may not be reliable in the next period. Therefore, we prefer a machine learning tool to build a more flexible model. It is worth noting that the machine learning tool also tends to distinguish $C_T\Delta T$ from $C_R\Delta t$ to perform accurate mapping from BWS to temperature; therefore, an appropriate $\Delta t$ will also improve the accuracy of the model.

Based on the samples from day 10 to 95, the values of $|C_R\Delta t|$ and $|C_T\Delta T|$ versus $\Delta t$ are shown in Fig. 2a. The values $|C_R\Delta t|$ are averaged from all the “NO” testing periods from day 10 to 95, and values $|C_T\Delta T|$ are averaged from all the “AF” or “AR” periods from day 10 to 95 based on different $\Delta t$. When $\Delta t$ is approximately 2.5h or 5.6h, the temperature stops falling or rising, respectively. Fig. 2b shows that from 2.5h to 5.6h, the largest ratio for AR periods appears at approximately 4h. We also hope that the ratios for
periods AR and AF are close to each other for less learning bias. Thus, Δt was selected to 4h.

The LSTM network we developed consists of a two-channel input layer, an LSTM layer with 200 hidden units, a fully connected layer, and a regression output layer. Based on (2), we set the Bragg wavelength and wavelength shift [λ_B, Δλ_B] as two-channel features to the input layer. The LSTM layer contains blocks corresponding to every time step, passing information from all previous samples regardless of the length of the sequence, and the gate mechanism controls the addition or removal of information at each time step. This is how LSTM learns long-term dependencies. The number of hidden units determines the amount of information that LSTM remembers over time steps; thus, we set 200 as an empirical number to prevent overfitting. The wavelength-to-temperature mapping is actually a regression problem, so the fully connected layer is followed by a regression output layer. We set the training target as T rather than ΔT to mitigate the error accumulated by adding the predicted ΔT together. Based on (1), the reactor state series s is determined by the predicted [T, ΔT].

The network was trained on the first 95 days for 100 epochs and tested on the remaining 85 days. Fig. 3 shows the drift mitigation and anomaly identification diagram. Data pre-processing was carried out to find the Bragg wavelength (λ_B) and wavelength shift (Δλ_B) in a specific time period (Δt as mentioned above).

![FIGURE 3. Drift mitigation and anomaly identification diagram.](image)

If the reactor state is “AD,” the reactor operates at a lower power, and the radiation level and temperature are steady in the lower range. Thus, neither temperature nor radiation-related terms were sufficiently large to estimate the coefficients. As this study focuses on drift mitigation (NO state) and anomaly identification (AF and AR states), we omitted AD periods.

### IV. RESULTS AND DISCUSSION

As mentioned in Section 3, both temperature and radiation effects, as two key factors, contribute to the wavelength shift of the FBG temperature sensor. We compared the predicted and measured temperatures to evaluate the drift-mitigation results, as shown in Fig. 4a. The AD periods were omitted, as explained in Section 3. Day 1-95 and 96-180 are the training and testing periods, respectively. Once trained by data from day 1-95, the network has never been updated over the entire testing period. Fig. 4b shows the prediction accuracies for various error tolerances. Accuracy confidence levels over 80.2%, 90%, and 95% were achieved within error tolerances of ±0.95°C, ±2.63°C and ±6.49°C, respectively.

![FIGURE 4. (a) Temperature predicted by LSTM from day 95 to day 180. (b) Prediction accuracies over different error tolerances from ±0.1°C to ±25°C.](image)

It is worth noting that we did not update our LSTM network using new samples after the training period because we hope to see if our network can be flexible to the continuous evolution of sensor characteristics. It can be observed from Fig. 1d that the wavelength drifting rates in the training period (day 1-95) are different from the testing period and continuously change over such a long-term testing. The results in Fig. 4a show that our LSTM network can still achieve the mapping from wavelength to temperature even after day 150. This proves the potential of the machine learning tool to be flexible for the complicated evolution of sensor characteristics.

Table 1 lists the anomaly identification accuracies based on the predicted temperatures. Our LSTM network achieved 100% anomaly event identification and over 96.6% and 94.3% detection accuracy for samples under AF and AR states, respectively. Most of the missed or false alarm samples are around “AF” or “AR” testing periods. About 0.85% and 2.12% samples were incorrectly detected as “AF” or “AR”, respectively.

| Anomaly          | Events Identified | Samples Detected | False alarm |
|------------------|-------------------|------------------|-------------|
| Anomaly-Falling (AF) | 100%             | 96.6%            | 0.85%       |
| Anomaly-Rising (AR) | 100%             | 94.3%            | 2.12%       |

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Because anomaly detection is based on the temperature predicted by the LSTM network, as shown in Fig. 3, the detection accuracy depends on the mapping accuracy from wavelength to temperature.

To improve the performance of the LSTM network, updating the network parameters with new samples is still a good option, especially for real-time applications. The updating process can be repeated after a specific period of time to collect sufficient new samples. Although other temperature sensors such as thermocouples are required for reference, FBGs still have many advantages such as less response time, high sensitivity, less temperature leakage through cabling, and the ability to monitor the local temperature [16,17].

Another factor, $\Delta t$ also plays an important role because it controls the length of the time period to calculate wavelength and temperature variation. The selection of $\Delta t$ is based on training samples, as described in Section 3, but in real-time application, the proper value of $\Delta t$ may vary over time. A possible solution is to update the network by different $\Delta t$ values and estimate a proper range after a specific time period. This can be included in the updating process described above. Another solution is to train an end-to-end model to directly map the Bragg wavelength or amplitude to temperature, skipping the calculation of the relative wavelength shift.

V. CONCLUSION
This paper demonstrates the resilience of fiber sensors in the extremely harsh environment of an operating nuclear reactor core and the effectiveness of the machine learning approach. This application of an LSTM neural network shows that radiation-induced sensor drifts and overall FBG peak wavelength degradation can be effectively mitigated. The machine learning approach shows great potential for improving the measurement accuracy for anomaly identification and overall reactor performance monitoring.

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