

Research Paper

Deep-learning-enabled fiber Bragg grating high-temperature sensing with accuracy improvement

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ABSTRACT

Femtosecond-laser-inscribed fiber Bragg gratings (FBGs) have shown great potential for high-temperature sensing, yet accurate demodulation under extreme conditions remains challenging. Over a wide temperature range, the spectral response of FBGs becomes increasingly nonlinear, which reduces the accuracy of conventional fitting models. Sapphire fiber Bragg gratings (SFBGs) can operate at temperatures up to 1900 °C, but their multimode interference (MMI) effect and strongly nonlinear spectral behavior make high-accuracy temperature demodulation more difficult. To address these issues, a deep-learning demodulation architecture based on a convolutional attention bidirectional long short-term memory network (CAB-LSTM) is proposed. To build spectral training datasets with reliable temperature labels, fiber grating sensors with thermal responses matched to that of a thermocouple were designed and fabricated. A geometric tuning method was adopted to optimize the sensor packaging, and the package diameters of the FBG and SFBG sensors were controlled at 2.3 and 2.1 mm, respectively. This design improved the physical consistency between the spectral measurements and the reference-temperature labels under the tested heating conditions. Experimental results show that the standard deviation (SD) of the FBG sensor remained within 0.72 °C at 700 °C. For the SFBG sensor, the SD values were 1.007 °C at 800 °C and 1.228 °C at 1600 °C. With physically aligned training data and the CAB-LSTM architecture, the proposed method provides an effective solution for real-time and high-accuracy temperature monitoring in extreme industrial environments. Under the tested 10 Hz acquisition condition, the complete update cycle was approximately 98 ms after the initial 3.1 s buffer-filling stage.

1. Introduction

High-temperature measurement is of great importance in critical industrial fields, including aerospace propulsion, gas turbines, metallurgical processing, and advanced nuclear energy systems. In enclosed or obstructed hot zones, in situ monitoring of hot components is essential for safe and reliable operation [1]. Although thermocouples remain one of the most widely used high-temperature sensors in engineering, they often suffer from drift, limited lifetime, and repeated calibration problems under ultra-high-temperature, long-term service, or corrosive conditions [2]. Infrared thermography has the advantage of noncontact measurement. However, it relies on surface radiation

information and line-of-sight access, which makes it difficult to apply in enclosed spaces, obstructed regions, or internal temperature-field measurements [3]. Therefore, under enclosed, strong electromagnetic interference, and extreme high-temperature conditions, fiber-optic sensing technology shows greater application potential because of its remote transmission capability, immunity to electromagnetic interference, and compact size [4]. Owing to these advantages, fiber-grating and fiber-interferometric structures have been widely applied to temperature and multi-parameter measurement in diverse environments [5,6].

Femtosecond-laser-inscribed fiber Bragg gratings (FBGs) have become an important approach for temperature sensing in harsh environments because of their high-temperature resistance, small size, and

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reusability [7]. However, the operating temperature of conventional silica-based FBGs is limited by the intrinsic thermal tolerance and thermal stability of the material. Their long-term operating temperature is usually insufficient for extreme high-temperature applications [8]. Even regenerated FBGs can only extend the upper temperature limit to a higher but still restricted range [9]. To overcome the temperature limit of silica, researchers have further introduced femtosecond laser inscription into single-crystal sapphire fibers, leading to sapphire fiber Bragg gratings (SFBGs). SFBGs can operate at temperatures approaching 1900 °C and therefore show clear advantages in extreme high-temperature measurement [10]. Notably, SFBGs have recently advanced from single-point devices toward distributed industrial instrumentation. Femtosecond-laser point-by-point inscription has produced large-scale cascaded first-order SFBG arrays with enhanced reflectivity and simplified spectral signatures [11], and such arrays have been successfully deployed in the submerged entry nozzle of a continuous-casting line, providing distributed thermal profiling of molten-steel transfer with characterization up to 1600 °C and 40-h stability under extreme conditions [12]. These results mark an important step toward practical ultra-high-temperature sensing in real production environments. However, their lack of a conventional core-cladding structure leads to strong multimode propagation, which broadens the reflection spectrum, distorts peaks, and increases modal interference. These effects make high-accuracy demodulation more difficult [13–15].

In high-temperature fiber grating demodulation, increasing temperature introduces stronger spectral nonlinearity and degrades the stability of conventional center-wavelength extraction methods [16]. This problem becomes particularly pronounced above 1000 °C, where the nonlinear thermo-optic effect and thermal expansion make the wavelength-temperature response difficult to describe using linear or low-order polynomial models [17]. Moreover, most existing calibration methods rely on static measurements at discrete temperature points, which cannot capture the continuous spectral evolution and transient characteristics during dynamic heating processes [18]. Under extreme high-temperature conditions, these effects are coupled together and become major limitations to further improvement in demodulation accuracy [19].

In recent years, machine learning and deep learning have been gradually introduced into FBG demodulation and have shown clear potential over traditional peak-tracking methods. More broadly, artificial-intelligence-driven data processing has recently been scaled to engineering-level fiber-optic sensing systems [20]. Deep convolutional networks have been used to directly learn the temperature mapping from full FBG spectra [21]. Dilated convolutional networks have been applied to improve spectral feature extraction [22]. Hybrid architectures such as CNN-LSTM and Bi-LSTM further introduce temporal modeling to improve demodulation performance under overlapping-spectrum or dynamic-spectrum conditions [23,24]. In particular, LSTM-based models can map full interferometric spectra directly to the measurand and overcome free-spectral-range limitations [25]. In addition, machine-learning methods have been used for temperature-strain discrimination, multiparameter decoupling, and calibration compensation in FBG systems [26–28]. SFBG demodulation research has largely remained focused on multimode-signal stabilization and conventional spectral post-processing. Representative approaches include added multimode lead-in fibers for mode stabilization [29], long-wavelength-edge detection and cross-correlation for wavelength retrieval, and single-mode or other modal-filtering sapphire waveguide designs to suppress higher-order modes [30,31]. These methods can improve spectral stability, but they remain sensitive to peak splitting, modal drift, fabrication-induced loss, and the length constraints of practical single-mode structures. A particularly promising route changes the interrogation domain altogether. In dispersive microwave-photonics interrogation, wavelength is mapped to delay and the Bragg shift is retrieved as a time-delay shift, which is inherently robust to multimode-induced

spectral distortion and yields 0.02 °C resolution up to 1050 °C without a high-resolution OSA [32]. This demonstrates that sensing resolution can be decoupled from spectral-acquisition resolution by transforming the domain in which the measurement is made. Along this direction, all-optical in-sensor computing has further enabled nanosecond-latency, multi-parameter fiber sensing [33]. More recently, machine learning has been introduced as a data-driven post-processing tool; for example, fast and robust demodulation of temperature from sparse sapphire FBG spectra has been demonstrated with machine learning [34], indicating that ML can compensate for under-sampled spectra and improve vibration robustness. However, these demonstrations still depend on carefully engineered optical front ends and sensor-specific datasets collected at discrete temperatures, so their generalization to continuously varying, strongly multimodal spectra under dynamic heating remains limited.

This work develops a calibration and demodulation method for high-temperature FBG and SFBG sensing. For calibration, the package geometry is selected to match the thermal response time constant of the reference thermocouple. Together with timestamp alignment, this design allows spectra and reference temperatures to be paired during a single continuous heating run from room temperature to the target temperature, avoiding repeated equilibration holds at discrete temperature setpoints. For demodulation, CAB-LSTM combines a 1D-CNN for local spectral feature extraction, an attention module for weighting temperature-sensitive features, and a Bi-LSTM for modeling correlations across successive spectra. The network uses the resulting features to estimate the temperature at the final time step of the input sequence. The results show that the method can achieve high-accuracy and high-stability temperature demodulation over a wide temperature range.

2. Sensor fabrication and experimental setup

2.1. Sensor fabrication and experimental setup

To meet the measurement requirements of different temperature ranges, two types of fiber Bragg grating sensors, i.e., FBG and SFBG, were fabricated in this work. Both sensors were inscribed using the same femtosecond laser line-by-line writing system. A frequency-doubled femtosecond laser amplifier (Pharos, Light Conversion), with a central wavelength of 514 nm, a pulse width of 290 fs, and a repetition rate of 200 kHz, was used as the inscription source. The femtosecond laser beam was focused into the fiber using a 100× Leica oil-immersion objective with a numerical aperture (N.A.) of 1.25. A three-axis air-bearing high-precision translation stage (Aerotech; ABL15010, ANT130LZS, and ANT130V-5) was employed to precisely control the grating period, and a high-resolution CCD was used to monitor the inscription process in real time.

As shown in Fig. 1(a), the FBG sensor was inscribed in a standard single-mode silica fiber after coating removal. As shown in Fig. 1(a3). Its central wavelength, signal-to-noise ratio (SNR), and full width at half maximum (FWHM) were 1549.51 nm, 18.34 dB, and 0.783 nm, respectively. As shown in Fig. 1(b), the SFBG sensor was inscribed in a single-crystal sapphire fiber with a diameter of 100 μm. As shown in Fig. 1(b3). Its central wavelength, SNR, and FWHM were 1530.93 nm, 11.78 dB, and 1.565 nm, respectively. The packaging configurations in Figs. 1(a) and 1(b) correspond to the intended operating temperature ranges of the two sensors. As shown in Figs. 1(a1) and 1(a2), the silica-based FBG was packaged in a ceramic tube for measurements up to approximately 1000 °C, providing mechanical protection and thermal stability. As shown in Figs. 1(b1) and 1(b2), the SFBG was packaged in a sapphire tube for measurements up to 1900 °C, where the superior high-temperature capability of sapphire enables operation in the harsher thermal environment.

To ensure that the sensors and the reference thermocouple experienced the same thermal field as closely as possible, the packaged sensor probes and the thermocouple were placed side by side in the central

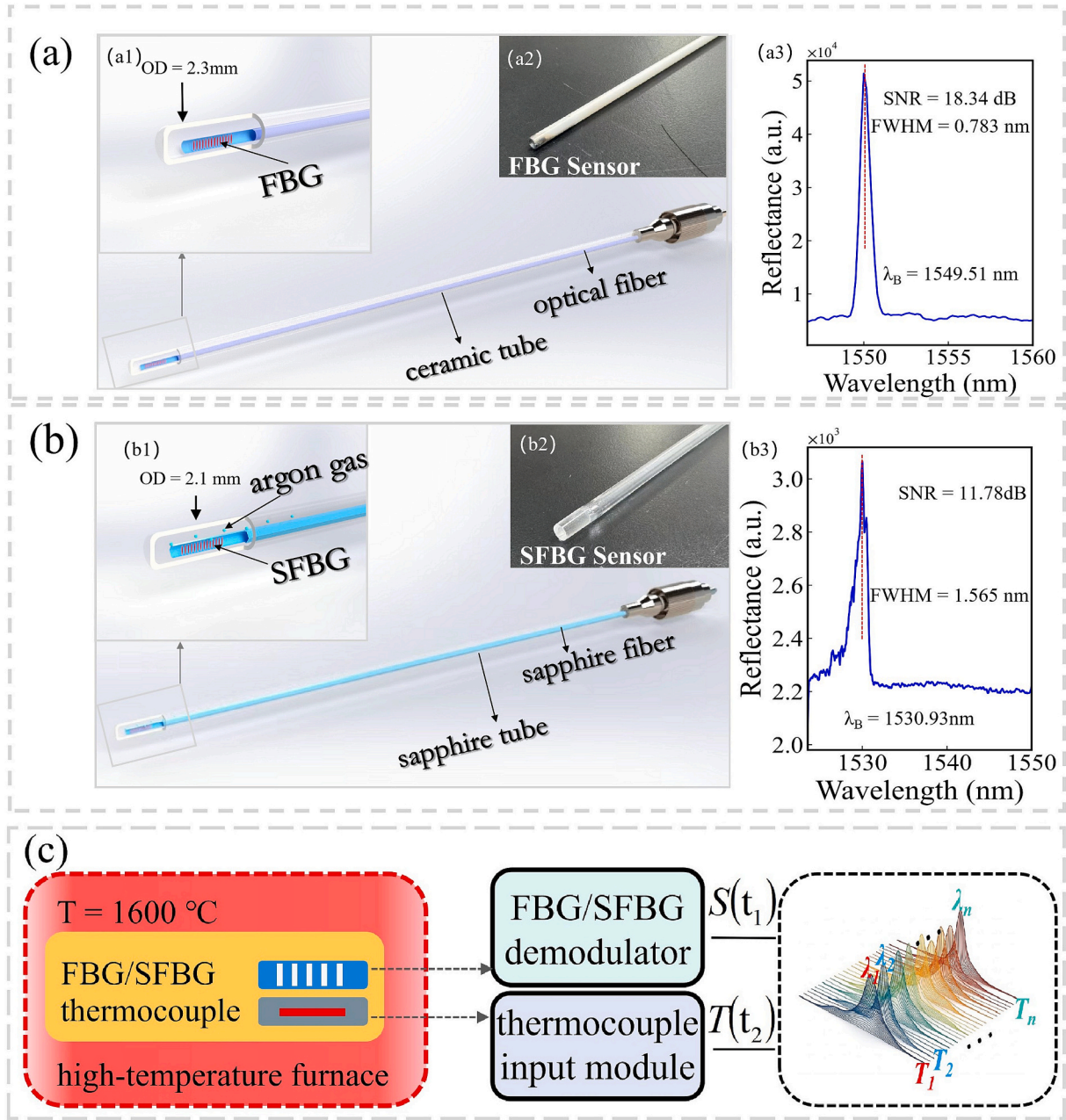


Fig. 1. Fabrication and experimental setup of the FBG and SFBG sensors: (a) ceramic-packaged FBG sensor, with (a1) a schematic of the FBG encapsulated in the ceramic tube (OD = 2.3 mm), (a2) a photograph of the fabricated sensor, and (a3) its reflection spectrum ($\lambda_B = 1549.51$ nm, FWHM = 0.783 nm, SNR = 18.34 dB); (b) sapphire-packaged SFBG sensor, with (b1) a schematic of the SFBG sealed in an argon-filled sapphire tube (OD = 2.1 mm), (b2) a photograph of the fabricated sensor, and (b3) its reflection spectrum ($\lambda_B = 1530.93$ nm, FWHM = 1.565 nm, SNR = 11.78 dB); (c) schematic of the high-temperature measurement system, showing the synchronous acquisition of the spectral data $S(t_1)$ from the FBG/SFBG demodulator and the temperature data $T(t_2)$ from the thermocouple input module in a furnace at 1600 °C.

constant-temperature zone of the furnace. The grating sensing region and the thermocouple junction were positioned side by side at the same axial location in the center of the furnace, with an approximate lateral separation of 1–2 mm. Considering the applicable temperature range and high-temperature stability of different thermocouples, a K-type thermocouple was used as the reference for the FBG sensor, while a B-type thermocouple was used as the reference for the SFBG sensor. During the experiment, the reflection spectra of the sensors were acquired in real time using an in-house-developed interrogator based on a swept-wavelength laser and a photodetector. The interrogator operated over 1522–1572 nm with a wavelength accuracy of 5 pm and a raw wavelength sampling interval of 20 pm. Its built-in interpolation

algorithm reconstructed the acquired spectra on a 1 pm wavelength grid for subsequent processing. The 1 pm value describes the interpolated output spacing and should be distinguished from the wavelength measurement accuracy. At the same time, the temperature data from the thermocouples were also recorded. Each heating experiment was repeated 10 times to improve the stability and statistical reliability of the dataset. As shown in Fig. 1(c), thermal-response matching and temporal alignment were performed between the spectral data $S(t_1)$ from the interrogator and the temperature data $T(t_2)$ from the thermocouple. This process enabled the construction of a spectral dataset with accurate temperature labels for subsequent CAB-LSTM model training. For reference-temperature labeling, the Class 1 K-type thermocouple has

a standard tolerance of $\pm 1.5^\circ\text{C}$ from -40 to 375°C and $\pm 0.004|t|^\circ\text{C}$ from 375 to 1000°C according to IEC 60584-2 and GB/T 16839.2-1997. This corresponds to $\pm 2.8^\circ\text{C}$ at 700°C and $\pm 3.6^\circ\text{C}$ at 900°C . For the B-type thermocouple, the Class 2 standard tolerance is $\pm 0.0025|t|^\circ\text{C}$ over 600 – 1700°C , corresponding to $\pm 4.0^\circ\text{C}$ at 1600°C . Here, t denotes the temperature in degrees Celsius. These values are standard tolerance limits and do not constitute a complete uncertainty budget for the measurement system. According to the PR322C furnace manual, the axial temperature gradient is no more than 0.5°C per 10 mm within ± 20 mm of the maximum-temperature position, and the specified temperature stability is no more than $0.1^\circ\text{C}/\text{min}$ and $0.5^\circ\text{C}/6$ min.

2.2. Thermal response modeling and geometric optimization

In this work, the transient thermal response of the sensor packaging system is modeled based on transient heat-transfer theory. For the ceramic and sapphire packaging tubes used in this study, the thermal conductivity is relatively high ($k > 25 \text{ W}/(\text{m}\cdot\text{K})$), and the characteristic size is on the millimeter scale ($D \approx 2$ mm). Under coupled convection-radiation boundary conditions, the calculated Biot number is always lower than 0.02 , that is, $Bi \ll 0.1$. Therefore, the lumped-capacitance method can be used as a first-order approximation for the packaging structure. In this approximation, the temperature inside the package is assumed to be nearly uniform, and the internal conductive thermal resistance is negligible compared with the external heat-transfer resistance at the surface. Under these assumptions, the energy conservation equation of the sensor packaging structure can be written as follows:

$$\rho c_p V \frac{dT}{dt} = -h_{\text{eff}} A_s (T - T_\infty) \quad (1)$$

where ρ , c_p , V , and A_s denote the density, specific heat capacity, volume, and surface area of the packaging material, respectively. T is the instantaneous temperature of the package, and T_∞ is the ambient temperature. The effective heat-transfer coefficient h_{eff} accounts for the combined effects of convective and radiative heat transfer, and can be expressed as:

$$h_{\text{eff}} = h_{\text{conv}} + \sigma \epsilon (T^2 + T_\infty^2) (T + T_\infty) \quad (2)$$

where h_{conv} is the effective convective heat-transfer coefficient, σ is the Stefan-Boltzmann constant, and ϵ is the surface emissivity. Although h_{eff} varies with temperature and thus shows nonlinear behavior, the objective of this work is not to maintain a strictly constant absolute response over the full temperature range. Instead, the goal is to make the instantaneous thermal response of the fiber sensor as consistent as possible with that of the reference thermocouple under the same thermal environment. Since the two sensors are placed together in the constant-temperature zone of the furnace and experience similar convection-radiation boundary conditions, the difference in their dynamic responses is mainly determined by thermal inertia. In this work, the geometric tuning parameter D is defined as the outer diameter of the packaging tube. For this slender cylindrical packaging structure, whose response is mainly governed by the outer diameter, the characteristic length can be approximately written as:

$$L_c = \frac{V}{A_s} \approx \frac{D}{4} \quad (3)$$

The time constant is given by:

$$\tau = \frac{\rho c_p D}{4 h_{\text{eff}}} \quad (4)$$

Eq. (4) shows that the thermal inertia of the sensor can be directly adjusted through the packaging diameter D . Therefore, matching the time constant by tuning the outer diameter of the package can effectively reduce the temperature-label deviation caused by inconsistent

thermal inertia during the dynamic heating process.

The model explicitly includes the inner diameter of the tube ($D - 0.5$ mm), the air or argon in the gap between the fiber and the inner wall, and axial conduction along the fiber, tube wall, and end cap. Heat transfer across the gas gap was calculated directly in the gas domain without an assumed contact resistance.

The finite-element model was implemented in COMSOL Multiphysics 6.4 as a two-dimensional axisymmetric transient heat-transfer model. Two assemblies were considered: a $125 \mu\text{m}$ silica FBG in an air-filled alumina (99.5%) tube, and a $100 \mu\text{m}$ single-crystal sapphire FBG in an argon-filled sapphire tube. The tube wall and the closed end cap were both 0.25 mm thick, so that the inner diameter was $D - 0.5$ mm. The grating length was 5 mm, with 0.5 mm fiber extensions at both ends and a 0.05 mm gap between the fiber tip and the end cap. The outer diameter D was scanned from 0.7 to 3.5 mm in steps of 0.2 mm, and the grating temperature was taken as the volume average over the 5 mm sensing region. The initial temperature was 25°C , and at $t = 0$ the surrounding gas and the effective furnace-wall radiation temperatures were stepped to 1000°C . The inward heat flux at the outer surface and the closed end cap was

$$q_{\text{in}} = h(T_g - T) + \epsilon \sigma (T_{\text{rad}}^4 - T^4) \quad (5)$$

where $h = 25 \text{ W}/(\text{m}^2\cdot\text{K})$ was taken as an engineering baseline for natural convection around horizontal miniature tubes at atmospheric pressure without forced flow, ϵ is the effective gray-body emissivity (0.80 for alumina and 0.30 for sapphire), σ is the Stefan-Boltzmann constant, and $T_g = T_{\text{rad}} = 1273.15 \text{ K}$. The rear cross-section was treated as adiabatic to represent the local response within a uniform-temperature furnace zone.

Based on the above theoretical analysis, finite element analysis (FEA) was further carried out to determine the optimized package sizes of the two types of sensors. Fig. 2 shows the relationship between the thermal time constant τ and the package diameter D for ceramic-packaged and sapphire-packaged sensors. According to Eq. (4), τ is expected to vary linearly with D when h_{eff} is approximated as a constant. However, the FEA results show that the actual τ increases superlinearly with increasing D . This is mainly because both the convective heat-transfer coefficient and the radiative heat-transfer term vary with geometry and temperature in a coupled manner. At the same time, because

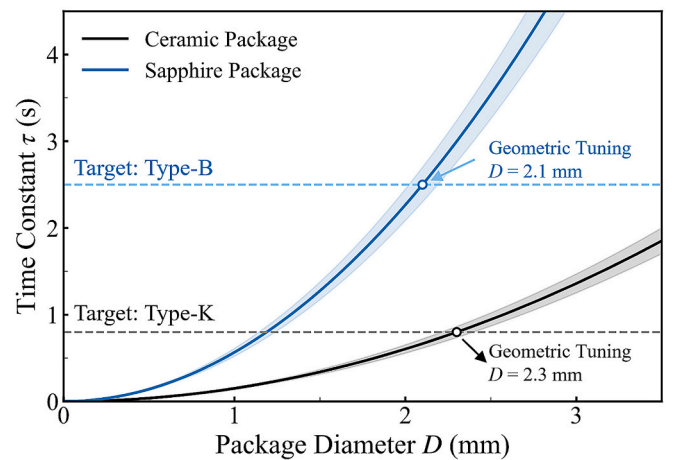


Fig. 2. Calculated thermal time constants τ as a function of packaging diameter (D) for ceramic- and sapphire-packaged sensors. Shaded bands represent deterministic parameter-scenario envelopes generated from the specified thermophysical-property and boundary-condition scenarios. Horizontal dashed lines indicate the target time constants of the standard K-type and B-type reference thermocouples. Open markers denote the geometrically tuned diameters selected in this work: $D = 2.3$ mm for ceramic-packaged FBG and $D = 2.1$ mm for the sapphire-packaged SFBG.

sapphire has a higher volumetric heat capacity (ρcp), the sapphire-packaged sensor always shows a larger thermal time constant than the ceramic-packaged sensor at the same diameter. This indicates that separate geometric optimization is necessary for FBG and SFBG sensors, rather than using a unified package size.

The shaded bands in Fig. 2 are deterministic parameter-scenario envelopes rather than statistical confidence intervals, and they do not imply a 95% confidence level. At each feasible diameter, the envelope was generated from three deterministic cases: a nominal case, a fast-response case, and a slow-response case. In the fast-response case, the convective heat-transfer coefficient, the solid thermal conductivity, and the gas thermal conductivity were each multiplied by 1.2, and the solid heat capacity by 0.9. In the slow-response case, the corresponding factors were 0.8, 0.8, 0.8, and 1.1. The upper and lower bounds of the band are the maximum and minimum time constants obtained from single-exponential fits of these three cases. The final optimized package size was determined by the intersection between the simulation curve and the target time constant of the reference thermocouple. The target time constants in Fig. 2 were taken from the measured transient responses of the standard thermocouples under the same experimental conditions. For the FBG sensor, whose design operating temperature did not exceed 900 °C, the optimized ceramic package diameter was $D = 2.3$ mm. The corresponding thermal time constant was about 0.8 s, which matched that of the K-type thermocouple. For the SFBG sensor, whose design operating temperature reached 1600 °C, the optimized sapphire package diameter was $D = 2.1$ mm. The corresponding thermal time constant was about 2.5 s, which matched that of the B-type thermocouple. These geometric tuning results made the dynamic responses of the fiber sensors more consistent with those of the reference thermocouples during transient temperature variation. This also provided the basis for constructing a physically consistent temperature-labeled dataset in the subsequent study.

2.3. Experimental validation of thermal response matching

Based on the previous thermal-response modeling and geometric tuning analysis, transient heating experiments were further carried out to verify the dynamic response matching between the optimized fiber

sensors and the reference thermocouples. In the experiment, a high-temperature furnace was used to heat the fiber sensors and the thermocouples simultaneously, and their transient response signals were recorded in real time. To evaluate the effectiveness of the geometric tuning strategy at multiple temperatures, transient-response experiments were conducted for the FBG sensor at 700 °C and 900 °C and for the SFBG sensor at 1000 °C and 1600 °C. The same package geometries, furnace position, and sensor arrangement were maintained in all tests. The validation curves represented controlled continuous-heating conditions. As indicated in Fig. 3, the instantaneous heating rate decreased as the set temperature was approached, ranging from approximately 120 to 8 °C/min for the FBG tests and from approximately 500 to 25 °C/min for the SFBG tests.

As shown in Fig. 3, the transient responses of the fiber sensors and the reference thermocouples were compared at four representative conditions. Figs. 3(a) and 3(c) show the FBG sensor with the K-type thermocouple at 700 °C and 900 °C, respectively, while Figs. 3(b) and 3(d) show the SFBG sensor with the B-type thermocouple at 1000 °C and 1600 °C, respectively. The two signals were aligned under a unified time reference. In all four cases, the fiber-sensor and thermocouple responses showed close agreement during the main heating stage and the subsequent approach to the final temperature. No systematic increase in response lag or dynamic mismatch was observed at the higher validation temperatures. These results indicate that the geometric tuning strategy maintained comparable transient behavior over the tested temperature points and heating-rate conditions. These experiments do not establish exact thermal-response matching at every temperature and heating rate across the full operating ranges. They provide validation at four representative temperature conditions and within the heating-rate ranges tested in this study.

3. CAB-LSTM network architecture

3.1. Network design

As shown in Fig. 4, the proposed CAB-LSTM network is used to establish the mapping from spectra to temperature. The input is a time-series spectral sequence of length 32, and the output is the temperature

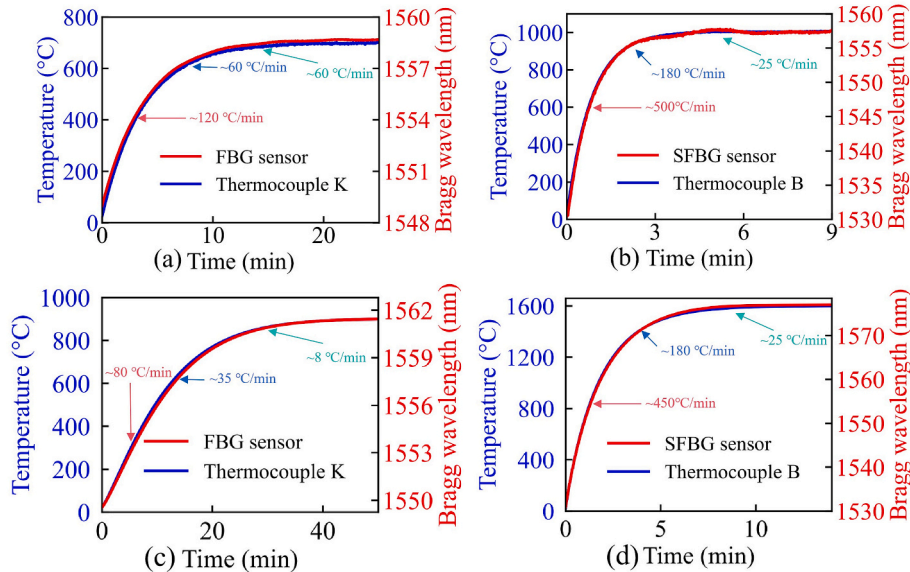


Fig. 3. Experimental validation of thermal-response matching at multiple temperatures and heating-rate conditions. Transient-response comparisons between the fiber sensors and the reference thermocouples are shown for (a) the FBG sensor and K-type thermocouple at 700 °C, (b) the SFBG sensor and B-type thermocouple at 1000 °C, (c) the FBG sensor and K-type thermocouple at 900 °C, and (d) the SFBG sensor and B-type thermocouple at 1600 °C. The red and blue curves represent the fiber-sensor and thermocouple responses, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

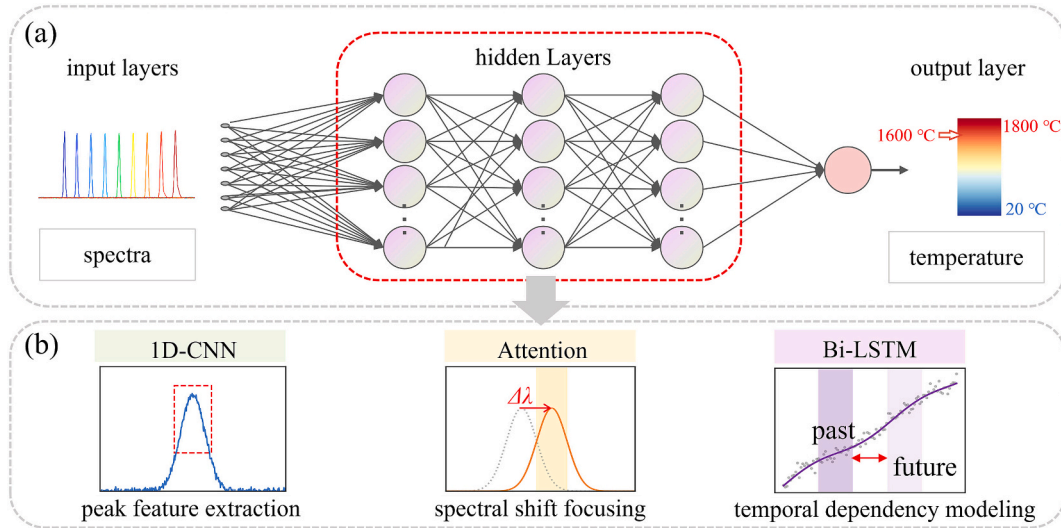


Fig. 4. Schematic diagram of the proposed CAB-LSTM network. (a) Overall architecture of the network, where the input is a time-series spectral sequence and the output is the temperature value. (b) Functional illustration of the three core modules, including peak-shape feature extraction by 1D-CNN, spectral weighting by the Attention module, and temporal modeling by Bi-LSTM.

at the last time step of the window. Let the i -th input sample be:

$$\mathbf{X}_i = [S(t_{i-31}), S(t_{i-30}), \dots, S(t_i)] \quad (6)$$

where $S(t_i)$ denotes the single-frame spectrum at time t_i . Each time step corresponds to a 1000-dimensional spectral vector. The network output is the temperature label $T(t_i)$ at the corresponding time.

The CAB-LSTM network consists of a 1D-CNN, an attention module, and a Bi-LSTM. The 1D-CNN uses two convolutional layers with 16 and 32 filters and kernel sizes of 5 and 3, respectively, to extract local features from each spectrum. The attention module adaptively weights these features to emphasize temperature-sensitive information. The Bi-LSTM contains 64 hidden units and models correlations among the spectral features in the 32-frame input window. The output layer maps the resulting features to the temperature $T(t_i)$ at the final time step. Unlike conventional peak-tracking demodulation, the proposed model does not require the temperature to be inferred from a single peak wavelength. Each input frame is represented by the complete sampled spectral vector. Because each input window ends at the latest acquired frame, the output associated with this frame uses only the current spectrum and the preceding 31 spectra. The bidirectional LSTM operates within this available historical window and does not access future measurements for the latest-frame output.

3.2. Dataset construction and preprocessing

Separate FBG and SFBG datasets were constructed by collecting spectra and reference thermocouple readings during continuous heating from room temperature to the respective target temperature. Thermal-response matching was used to reduce dynamic temperature discrepancies, and timestamp alignment paired the two measurements. Each heating run provided calibration data across the temperature range without intermediate equilibration holds. Multiple independent runs were collected for model training, validation, and testing. The same CAB-LSTM architecture was trained and evaluated separately on the two datasets.

The FBG dataset contained 10 independent experiments. Each experiment lasted 15 min and was sampled at 10 Hz, resulting in a total of 90,000 spectral frames. The SFBG dataset also contained 10 independent experiments. Each experiment lasted 6 min and was sampled at 10 Hz, resulting in a total of 36,000 spectral frames.

Each spectral frame contained 1000 sampling points. A sliding time

window with a length of 32 was used to construct the input samples, and the temperature at the end of the window was used as the label. The dataset was divided into training, validation, and test sets according to the experimental runs, with a ratio of 7:2:1. Different subsets corresponded to different experimental runs, and no overlapping time windows were shared across subsets, so as to avoid temporal information leakage. All input spectra were normalized to the range of [0,1] using min-max normalization based on the statistics of the training set. In addition to the original ten runs per sensor, four new heating runs were acquired for each of the same sensors and used exclusively for additional testing. For each sensor, the model weights and preprocessing parameters determined from the original data were kept fixed. These new runs were not used for retraining, fine-tuning, model selection, or updating normalization parameters.

3.3. Training configuration

The model was implemented in PyTorch and trained on an NVIDIA GeForce RTX 3050 Ti GPU. The Adam optimizer was used, with an initial learning rate of 1×10^{-3} . The mean squared error (MSE) was used as the loss function. The input sequence length was set to 32, and the batch size was set to 32. To reduce overfitting, a dropout layer was added after the Bi-LSTM output, with a dropout rate of 0.2. The maximum number of training epochs was set to 500. During training, learning rate decay and early stopping were adopted. The CAB-LSTM model contains 53,248 trainable parameters, corresponding to approximately 0.21 MB for FP32 weights (approximately 0.20 MiB). Inference was benchmarked with batch size one on an NVIDIA GeForce RTX 3050 Ti GPU. The 95th-percentile inference time for one 32-frame input window was 2.8 ms. Under the same acquisition conditions, the optical sweep required approximately 95 ms at the 95th percentile. The complete update cycle, measured from the start of the optical sweep to the completion of the corresponding temperature output, had a 95th-percentile duration of approximately 98 ms, corresponding to a nominal update capacity of approximately 10.2 Hz.

During online operation, the input sequence was processed using a sliding-window streaming implementation. The system first collected 31 frames to form the initial 32-frame window. At a 10 Hz acquisition rate, this initialization required approximately 3.1 s. After initialization, each newly acquired spectrum replaced the oldest frame in the buffer, and one temperature value was generated for the latest frame. Thus, the input window provides 3.2 s of historical spectral context, whereas the

steady-state output rate is determined by the acquisition rate and processing time rather than by the window length.

4. Results and discussion

To evaluate the temperature demodulation performance of the proposed CAB-LSTM network, 1D-CNN, DNN, and LSTM were selected as comparison models. The evaluation metrics were the root mean square error (RMSE) and the coefficient of determination (R^2). In this study, RMSE represents the root mean square difference between the model prediction and the corresponding reference thermocouple reading. Because the same reference thermocouple measurements were used for the proposed method and the comparison methods, RMSE provides a consistent measure for relative method comparison. The reported RMSE represents prediction error relative to the reference thermocouple rather than an independently established absolute temperature uncertainty. Fig. 5 shows the regression results of different models on the FBG dataset over the range of 25–900 °C. The RMSE values of 1D-CNN, DNN, and LSTM were 2.74 °C, 3.45 °C, and 3.95 °C, respectively. The corresponding R^2 values were 0.9981, 0.9970, and 0.9968, respectively. In comparison, the RMSE of CAB-LSTM was reduced to 0.89 °C, and the R^2 was increased to 0.9998. These results show that relying only on local spectral features, or only on temporal modeling, is not sufficient to achieve optimal demodulation performance. CAB-LSTM combines convolutional feature extraction, spectral attention weighting, and bidirectional temporal modeling, and therefore can more fully represent the nonlinear mapping between the FBG spectrum and temperature. Fig. 6 shows the residual analysis results of the FBG over the range of

25–900 °C. The mean residual over the full temperature range was -0.0003 °C, and the standard deviation was 0.4976 °C. The 95% limits of agreement ranged from -0.9755 °C to 0.9750 °C. At three representative temperature points, namely 25 °C, 400 °C, and 700 °C, the residual standard deviations were 0.413 °C, 0.617 °C, and 0.720 °C, respectively. These results show that the CAB-LSTM maintained an error distribution with nearly zero bias over the FBG operating temperature range, while the residual dispersion remained at a low level.

Fig. 7 shows the regression results of different models on the SFBG dataset over the range of 25–1600 °C. The RMSE values of 1D-CNN, DNN, and LSTM were 6.24 °C, 7.54 °C, and 7.90 °C, respectively. The corresponding R^2 values were 0.9983, 0.9978, and 0.9975, respectively. The RMSE of CAB-LSTM was further reduced to 1.80 °C, and the R^2 was improved to 0.9996. The SFBG RMSE of 1.80 °C was calculated as the root mean square difference between the CAB-LSTM predictions and the corresponding B-type thermocouple readings over the test dataset. It therefore represents prediction error relative to the reference thermocouple rather than an independently established absolute temperature uncertainty at 1600 °C. Compared with FBG, SFBG faces a wider temperature range, stronger multimode interference, and more pronounced nonlinear spectral changes. Therefore, its demodulation is more difficult. These results demonstrate that CAB-LSTM enables high-accuracy temperature demodulation from spectra acquired at a raw wavelength sampling interval of 20 pm. Fig. 8 shows the residual analysis results of the SFBG over the range of 25–1600 °C. The mean residual over the full temperature range was -0.04 °C, and the standard deviation was 0.98 °C. The 95% limits of agreement ranged from -1.97 °C to 1.89 °C. At three representative temperature points, namely 25 °C, 800 °C, and

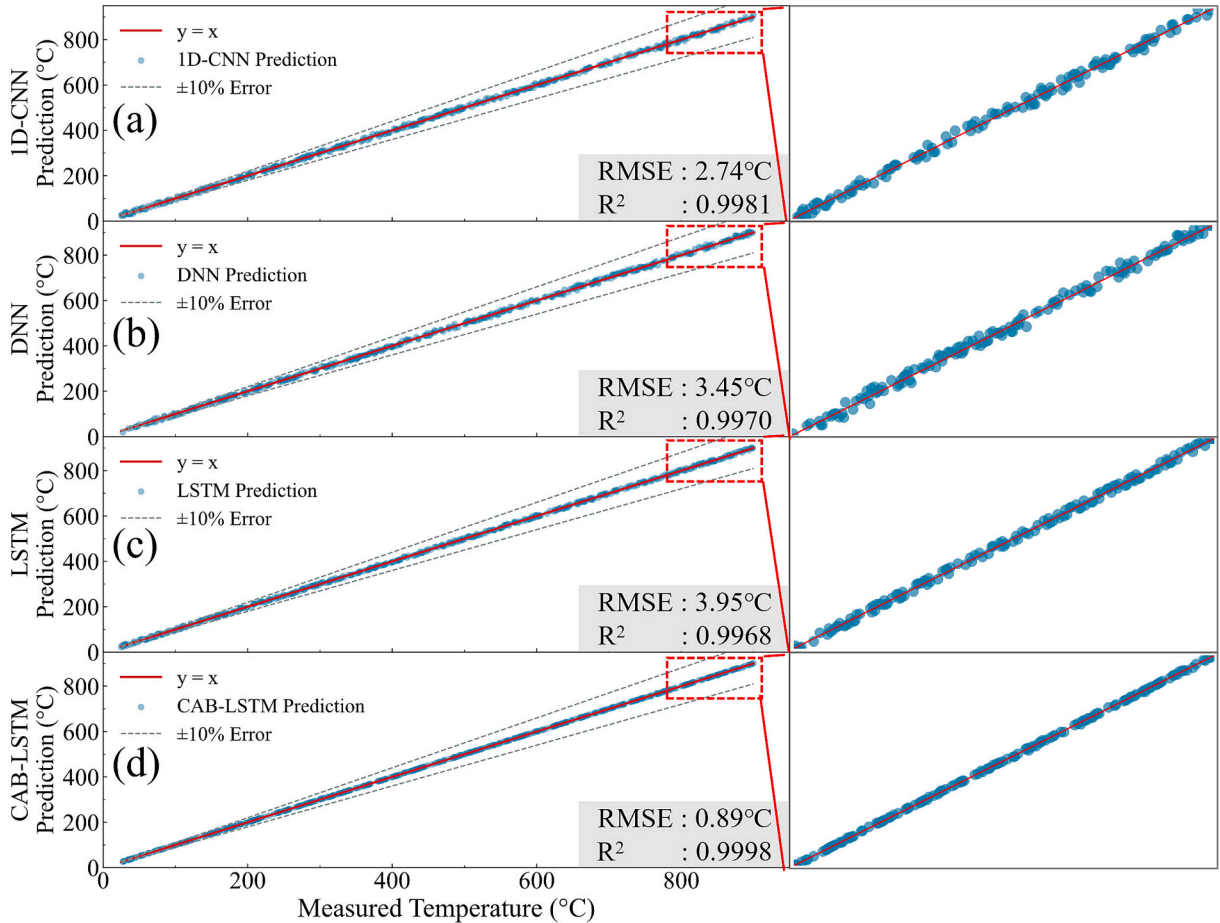


Fig. 5. Comparison of temperature prediction performance for the FBG sensor over the range of 25–900 °C: (a) 1D-CNN; (b) DNN; (c) LSTM; (d) CAB-LSTM. The enlarged plots on the right show the prediction details in the high-temperature region.

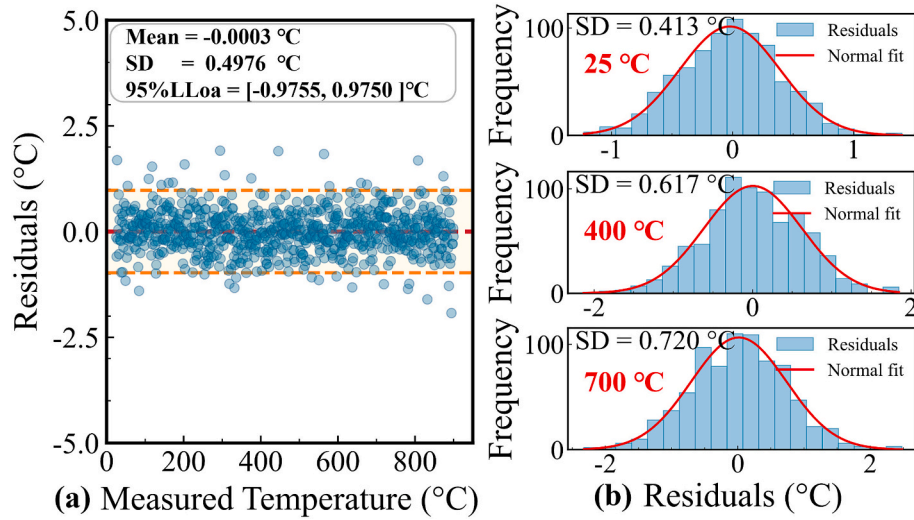


Fig. 6. Error distribution and residual analysis of the FBG sensor over the range of 25–900 °C: (a) Distribution of prediction residuals versus reference temperature over the full temperature range. The mean, standard deviation (SD), and 95% limits of agreement (95% LoA) are also given; (b) Residual histograms and Gaussian fitting results at three representative temperature points, namely 25 °C, 400 °C, and 700 °C.

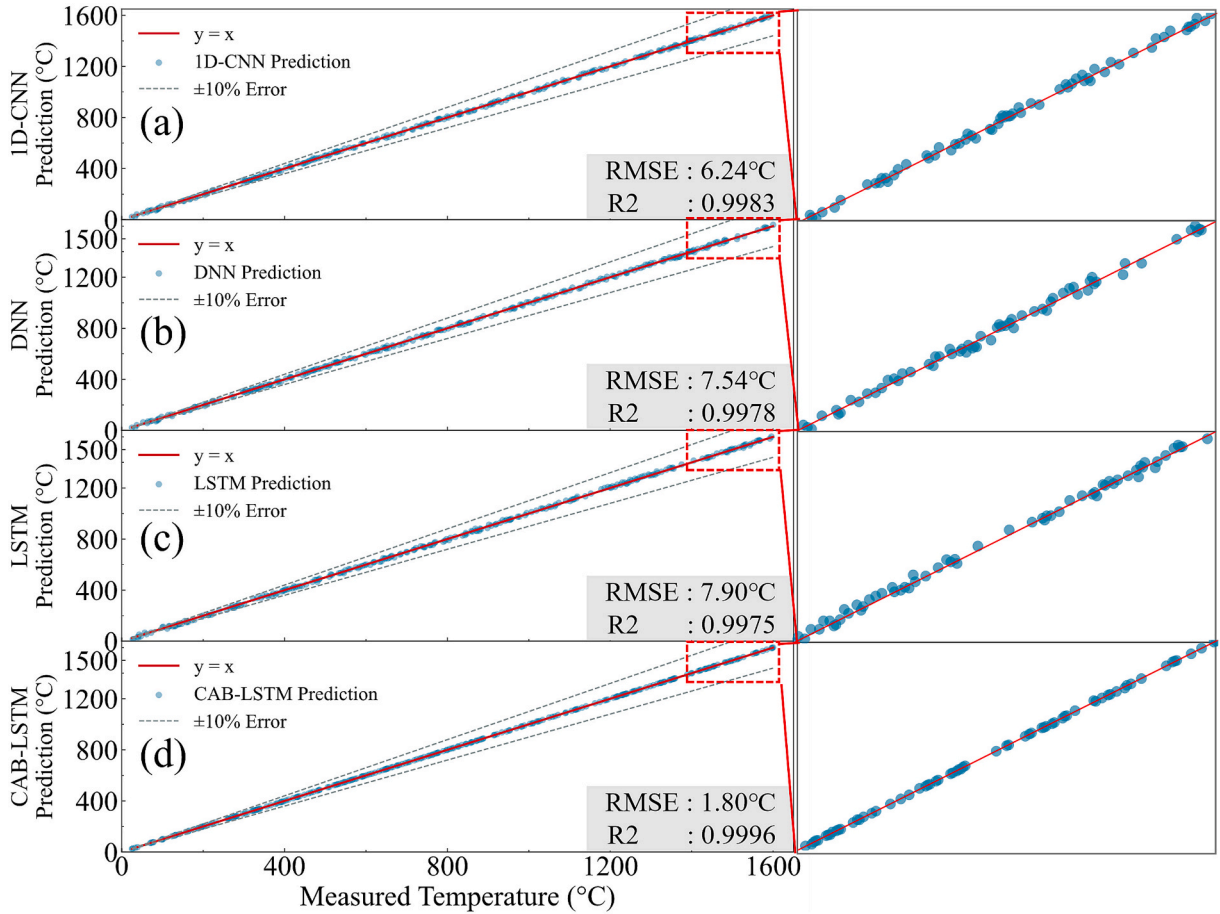


Fig. 7. Comparison of temperature prediction performance for the SFBG sensor over the range of 25–1600 °C: (a) 1D-CNN; (b) DNN; (c) LSTM; (d) CAB-LSTM. The enlarged plots on the right show the prediction details in the extreme high-temperature region.

1600 °C, the residual standard deviations were 0.765 °C, 1.007 °C, and 1.228 °C, respectively. These results show that the CAB-LSTM maintained an error distribution with nearly zero bias over the SFBG operating temperature range, while the residual dispersion remained at a low level.

For comparison, when the previously reported conventional peak-tracking method [30] was applied to the same SFBG test dataset under identical acquisition conditions, the demodulation error was approximately 5–6 °C. In contrast, the proposed CAB-LSTM method reduced the error by approximately 65%, demonstrating stronger robustness against

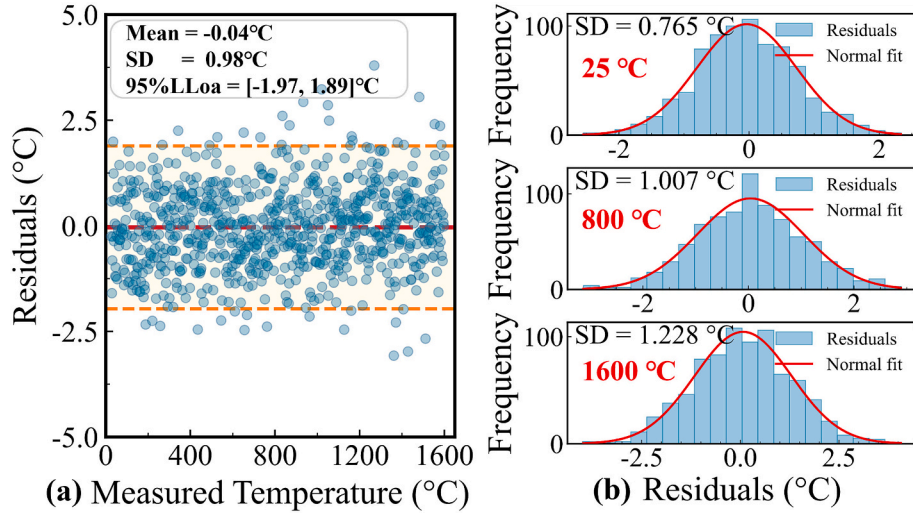


Fig. 8. Error distribution and residual analysis of the SFBG sensor over the range of 25–1600 °C: (a) Distribution of prediction residuals versus reference temperature over the full temperature range. The mean, standard deviation (SD), and 95% limits of agreement (95% LoA) are also given; (b) Residual histograms and Gaussian fitting results at three representative temperature points, namely 25 °C, 800 °C, and 1600 °C.

multimode-induced spectral distortion and nonlinear spectral evolution at high temperatures.

The test results of both sensors show that the CAB-LSTM significantly outperformed the comparison models under wide temperature-range conditions. Its performance improvement comes from the combined effect of three complementary modules. The 1D-CNN is used for local peak-shape feature extraction and multimode interference suppression. The Attention module is used to enhance temperature-sensitive spectral features. The Bi-LSTM is used to model the temporal dependence caused by thermal inertia and to reduce dynamic lag errors. It should be emphasized that the performance improvement comes not only from the network architecture itself, but also from the physically consistent labeled dataset constructed by the geometric tuning and temporal alignment strategies described above. Together, these two aspects support the high-accuracy temperature demodulation capability of the model under wide temperature ranges, strong nonlinearity, and high-noise conditions.

To further evaluate run-to-run robustness, four independent held-out heating runs were performed for each sensor using the fixed model weights and preprocessing parameters. No retraining, fine-tuning, model selection, or normalization update was performed using the held-out data. Each point in Fig. 9 represents the RMSE calculated from

one independent heating run. The mean run-wise RMSE was 0.92 °C with a standard deviation of 0.05 °C for the FBG sensor and 1.84 °C with a standard deviation of 0.18 °C for the SFBG sensor. The dashed lines indicate the mean RMSE values, and the shaded regions indicate the mean $\pm$ standard deviation across the four independent runs.

5. Conclusion

In this work, a high-accuracy temperature demodulation method combining geometric tuning and a CAB-LSTM network is proposed to address nonlinear response, multimode interference, and label deviation caused by thermal inertia in FBG and SFBG temperature demodulation under high-temperature and extreme high-temperature conditions. Based on transient heat-transfer theory and finite element analysis, the package sizes matching the thermal responses of the reference thermocouples were determined. The outer diameter of the ceramic package for the FBG was 2.3 mm, and the outer diameter of the sapphire package for the SFBG was 2.1 mm. The effectiveness of the thermal-response matching strategy was further verified by transient heating experiments at four representative temperature conditions, including the high-temperature endpoints of 900 °C for the FBG sensor and 1600 °C for the SFBG sensor. On this basis, a physically consistent spectrum-

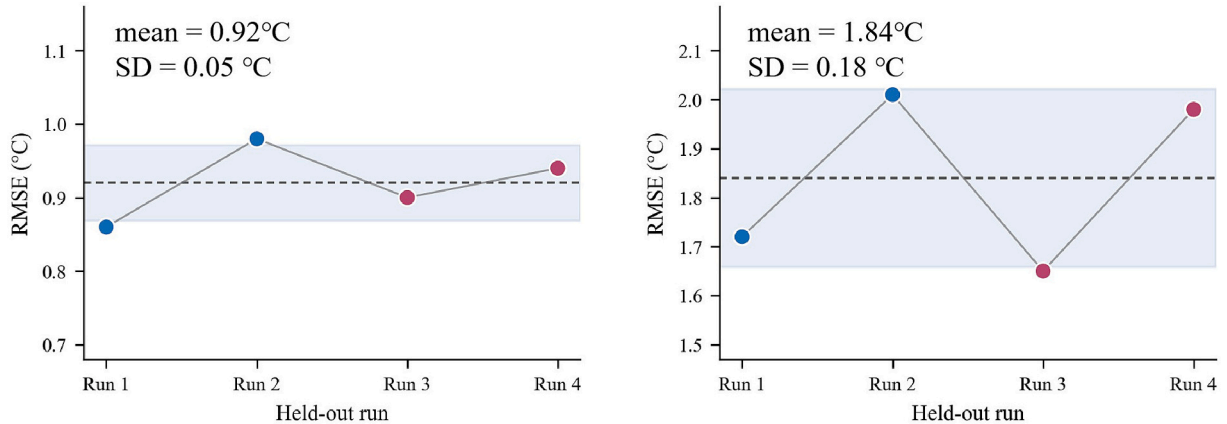


Fig. 9. Run-wise RMSE obtained from four independent held-out heating runs for the FBG and SFBG sensors. Each point represents one independent heating run. The dashed lines indicate the mean RMSE, and the shaded regions indicate the mean $\pm$ standard deviation across the four runs. The model weights and preprocessing parameters were fixed before these evaluations, and no retraining or fine-tuning was performed using the held-out data.

temperature labeled dataset was constructed, and a CAB-LSTM demodulation model composed of 1D-CNN, Attention, and Bi-LSTM was established. Experimental results show that, on the FBG dataset over 25–900 °C, the model achieved an RMSE of 0.89 °C and an R^2 of 0.9998. On the SFBG dataset over 25–1600 °C, it achieved an RMSE of 1.80 °C and an R^2 of 0.9996. Residual analysis further shows that the standard deviation of the FBG remained within 0.72 °C at representative temperature points, while the standard deviations of the SFBG were 1.007 °C and 1.228 °C at 800 °C and 1600 °C, respectively. Four additional independent heating runs per sensor, evaluated without model retraining, yielded mean RMSEs of 0.92 ± 0.05 °C for FBG and 1.84 ± 0.18 °C for SFBG (mean $\pm$ SD across runs). These results show that the proposed method can effectively improve the accuracy and stability of fiber grating temperature demodulation over a wide temperature range.

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Author contribution

Zhiwei Qin: Conceptualization, methodology development, sensor experiments, data acquisition and processing, model training and validation, result analysis, visualization, and writing - original draft. **Xizhen Xu:** Conceptualization, methodology design, supervision of sensor fabrication and high-temperature experiments, interpretation of results, project administration, and writing - review & editing. **Zhuoda Li:** Assisted with high-temperature experiments and spectral data acquisition. **Jingwei Zhang:** Assisted with experimental validation and result analysis. **Jia He:** Implemented the deep-learning model and supported software development. **Jiafeng Wu:** Assisted with sensor fabrication and packaging optimization. **Zhiyong Bai:** Assisted with experimental data collection. **Yiping Wang:** Provided scientific guidance on fiber-optic sensing. **Jun He:** Conceptualization, supervision of the overall research, resources and funding support, project administration, interpretation of results, and writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

- [1] S. Gao, X.Q. Zhang, L.W. Chen, Y. Cui, J. Jiang, Z.Z.Z. hang, P.F. Yu, C. Wang, Review: radiation temperature measurement methods for engine turbine blades and environment influence, *Infrared Phys. Technol.* 123 (2022) 104204, <https://doi.org/10.1016/j.infrared.2022.104204>.
- [2] E. Leonidas, S. Ayvar-Soberanis, H. Laalej, S. Fitzpatrick, J.R. Willmott, A comparative review of thermocouple and infrared radiation temperature measurement methods during the machining of metals, *Sensors* 22 (2022) 4693, <https://doi.org/10.3390/s22134693>.
- [3] P.R.N. Childs, J.R. Greenwood, C.A. Long, Review of temperature measurement, *Rev. Sci. Instrum.* 71 (2000) 2959–2978, <https://doi.org/10.1063/1.1305516>.
- [4] S. Ma, Y. Xu, Y. Pang, X. Zhao, Y. Li, Z. Qin, Z. Liu, P. Lu, X. Bao, Optical fiber sensors for high-temperature monitoring: a review, *Sensors (Basel, Switzerland)* 22 (2022) 5722, <https://doi.org/10.3390/s22155722>.
- [5] Z. Pan, M. Peng, Y. Gao, L. Wang, D. Fan, Y. Li, C. Zhou, Simultaneous measurement of temperature and depth using Fabry–Perot interferometers with draw-tower gratings, *Chin. Opt. Lett.* 23 (2025) 111202, <https://doi.org/10.3788/COL202523.111202>.
- [6] C. Jiang, J. Lai, Y. Wei, R. Xu, M. Chen, S. Qu, L. Yuan, Vector magnetic field and temperature measurement based on a magnetic fluid encapsulated HCF-TCF-HCF fiber structure, *Chin. Opt. Lett.* 24 (2026) 071201, <https://doi.org/10.3788/COL202624.071201>.
- [7] J. He, B.J. Xu, X.Z. Xu, C.R. Liao, Y.P. Wang, Review of femtosecond-laser-inscribed fiber Bragg gratings: fabrication technologies and sensing applications, *Photon. Sens.* 11 (2021) 203–226, <https://doi.org/10.1007/s13320-021-0629-2>.
- [8] D. Grobncic, C.W. Smelser, S.J. Mihailov, R.B. Walker, Long-term thermal stability tests at 1000 °C of silica fibre Bragg gratings made with ultrafast laser radiation, *Meas. Sci. Technol.* 17 (2006) 1009–1013, <https://doi.org/10.1088/0957-0233/17/5/S12>.
- [9] L. Polz, F.J. Dutz, R.R.J. Maier, H. Bartelt, J. Roths, Regenerated fibre Bragg gratings: a critical assessment of more than 20 years of investigations, *Opt. Laser Technol.* 134 (2021) 106650, <https://doi.org/10.1016/j.optlastec.2020.106650>.
- [10] D. Grobncic, S.J. Mihailov, C.W. Smelser, H. Ding, Sapphire fiber Bragg grating sensor made using femtosecond laser radiation for ultrahigh temperature applications, *IEEE Photon. Technol. Lett.* 16 (2004) 2505–2507, <https://doi.org/10.1109/LPT.2004.834920>.
- [11] F. Mumtaz, H. Tekle, B. Zhang, J.D. Smith, R.J. O'Malley, J. Huang, Highly cascaded first-order sapphire optical fiber Bragg gratings fabricated by a femtosecond laser, *Opt. Lett.* 48 (2023) 4380–4383, <https://doi.org/10.1364/OL.495138>.
- [12] F. Mumtaz, H.W. Tekle, B. Zhang, X. Li, S. Abraham, B. Mathis, J.D. Smith, R.J. O'Malley, J. Huang, Distributed sapphire fiber Bragg grating-based thermal profiling of submerged entry nozzles, *IEEE Trans. Instrum. Meas.* 74 (2025) 9530112, <https://doi.org/10.1109/TIM.2025.3593567>.
- [13] X.Z. Xu, J. He, C.R. Liao, K.M. Yang, K.K. Guo, C. Li, Y.F. Zhang, Z.B. Ouyang, Y. P. Wang, Sapphire fiber Bragg gratings inscribed with a femtosecond laser line-by-line scanning technique, *Opt. Lett.* 43 (2018) 4562–4565, <https://doi.org/10.1364/OL.43.004562>.
- [14] T. Habisreuther, T. Elsmann, Z.W. Pan, A. Graf, R. Willsch, M.A. Schmidt, Sapphire fiber Bragg gratings for high temperature and dynamic temperature diagnostics, *Appl. Therm. Eng.* 91 (2015) 860–865, <https://doi.org/10.1016/j.applthermaleng.2015.08.096>.
- [15] X.Z. Xu, J. He, C.R. Liao, Y.P. Wang, Multi-layer, offset-coupled sapphire fiber Bragg gratings for high-temperature measurements, *Opt. Lett.* 44 (2019) 4211–4214, <https://doi.org/10.1364/OL.44.004211>.
- [16] X.Z. Xu, Q.M. Tan, Z.D. Li, J.F. Wu, H. Li, J. He, Z.X. He, Y. Qin, T. Xu, Z.L. Ran, Y. P. Wang, J. He, Sapphire fiber Bragg gratings demodulated with cross correlation algorithm for long-term high-temperature measurement, *IEEE Sensors J.* 24 (2024) 7905–7911, <https://doi.org/10.1109/JSEN.2024.3358294>.
- [17] S.J. Mihailov, D. Grobncic, C. Hnatovsky, R.B. Walker, P. Lu, D. Coulas, H. Ding, Extreme environment sensing using femtosecond laser-inscribed fiber Bragg gratings, *Sensors* 17 (2017) 2909, <https://doi.org/10.3390/s17122909>.
- [18] J. He, X.Z. Xu, Z.D. Li, J.F. Wu, H. Li, Q.M. Tan, Z.X. He, Y.P. Wang, J. He, Stabilized ultra-high-temperature sensors based on inert gas-sealed sapphire fiber Bragg gratings, *ACS Appl. Mater. Interfaces* 14 (2022) 12359–12366, <https://doi.org/10.1021/acsami.1c24589>.
- [19] Z. Wang, W. Xu, L. Wang, C. Cui, C. Zhang, H. Zhou, H. Nong, Y. Deng, J. Yang, Y. Yu, Z. Zhang, High-temperature stability and demodulation techniques analysis of sapphire fiber Bragg grating sensor, *J. Lightwave Technol.* 43 (2025) 2312–2320, <https://doi.org/10.1109/JLT.2024.3492342>.
- [20] L. Shao, J. Zhang, X. Chen, D. Xu, H. Gu, Q. Mu, F. Yu, S. Liu, X. Shi, J. Sun, Z. Huang, X. Yang, H. Zhang, Y. Ma, H. Lu, C. Liu, C. Yu, Artificial intelligence-driven distributed acoustic sensing technology and engineering application, *Photonix* 6 (2025) 4, <https://doi.org/10.1186/s43074-025-00160-z>.
- [21] Z. Cao, S. Zhang, T. Xia, Z. Liu, Z. Li, Spectral demodulation of fiber Bragg grating sensor based on deep convolutional neural networks, *J. Lightwave Technol.* 40 (2022) 4429–4435, <https://doi.org/10.1109/JLT.2022.3155253>.
- [22] B. Li, Z.W. Tan, P.P. Shum, C. Wang, Y. Zheng, L.J. Wong, Dilated convolutional neural networks for fiber Bragg grating signal demodulation, *Opt. Express* 29 (2021) 7110–7123, <https://doi.org/10.1364/OE.413443>.
- [23] X. Lai, Y. Yang, Y. Li, J. Zhao, H. Wang, Demodulation algorithm for temperature and pressure sensing in side-hole fiber Bragg gratings using a CNN-LSTM network, *Opt. Express* 33 (2025) 7095–7112, <https://doi.org/10.1364/OE.550130>.
- [24] W. Liu, Y. Zhang, H. Chen, J. Sun, X. Zhao, Wavelength demodulation method for FBG overlapping spectrum utilizing bidirectional long short-term memory neural network, *Measurement* 242 (2025) 115918, <https://doi.org/10.1016/j.measurement.2024.115918>.
- [25] J. Hu, S. Zhang, M. Cai, M. Ma, S. Li, H. Chen, S. Yang, LSTM-assisted optical fiber interferometric sensing: breaking the limitation of free spectral range, *Light Sci. Appl.* 14 (2025) 392, <https://doi.org/10.1038/s41377-025-02008-4>.
- [26] K. Dey, N. Vangety, S. Roy, Machine learning approach for simultaneous measurement of strain and temperature using FBG sensor, *Sens. Actuators A Phys.* 333 (2022) 113254, <https://doi.org/10.1016/j.sna.2021.113254>.
- [27] S. Sarkar, D. Inupakutika, M. Banerjee, M. Tarhani, M. Shadaram, Machine learning methods for discriminating strain and temperature effects on FBG-based sensors, *IEEE Photon. Technol. Lett.* 33 (2021) 876–879, <https://doi.org/10.1109/LPT.2021.3055216>.
- [28] W. Sheng, X. Yin, J. Wen, G.D. Peng, Accurate and fast calibration for FBG demodulation based on deep learning and ensemble learning, *Opt. Laser Technol.* 172 (2024) 110476, <https://doi.org/10.1016/j.optlastec.2023.110476>.

- [29] S. Yang, D. Homa, H. Heyl, L. Theis, J. Beach, B. Dudding, G. Acord, D. Taylor, G. Pickrell, A. Wang, Application of sapphire-fiber-Bragg-grating-based multi-point temperature sensor in boilers at a commercial power plant, *Sensors* 19 (2019) 3211, <https://doi.org/10.3390/s19143211>.
- [30] M.H. Wang, P.S. Salter, F.P. Payne, A. Shipley, S.M. Morris, M.J. Booth, J.A.J. Fells, Single-mode sapphire fiber Bragg grating, *Opt. Express* 30 (2022) 15482–15494, <https://doi.org/10.1364/OE.446664>.
- [31] X.Z. Xu, J. He, J.F. Wu, R.X. Chen, F. Zhou, B.Z. Wang, Y.P. Zhang, Y.P. Wang, J. He, Single-mode helical sapphire Bragg grating for high-temperature sensing, *J. Lightwave Technol.* 43 (2025) 2982–2987, <https://doi.org/10.1109/JLT.2024.3503579>.
- [32] R. Jie, C. Zhu, F. Mumtaz, K. Dey, B. Zhang, J. Huang, Sapphire optical fiber Bragg grating sensors based on dispersive microwave-photonics frequency-time domain analysis, *J. Lightwave Technol.* (2026), <https://doi.org/10.1109/JLT.2026.3686929>.
- [33] Y. Tao, Y. Wan, Z. Long, W. Zhang, J. Du, Z. He, Nanosecond-latency all-optical fiber sensing with in-sensor computing, *Light Sci. Appl.* 15 (2026) 251, <https://doi.org/10.1038/s41377-026-02265-x>.
- [34] X. Liu, O. Alsalman, B. Liu, C. Zhu, Fast and robust demodulation of temperature from sparse sapphire fiber Bragg grating spectra with machine learning, *Opt. Express* 32 (2024) 13882–13893, <https://doi.org/10.1364/OE.515717>.