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AI-Assisted Brillouin-Based Distributed Temperature and Strain Sensing in Hybrid Polymer-Silica Optical Fibers for Harsh Environments

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Abstract

As a long-range, high-resolution monitoring technique of industrial and structural applications, distributed temperature and strain sensing (DTSS) based on Brillouin scattering has gained increasing attention. However, due to their superior spatial resolution, polymer optical fibers (POFs) suffer from poor performance in harsh environments where silicon fiber cannot be used, due to their susceptibility to environmental degradation, and poor thermal and strain cross sensitivity. Existing sensing cannot achieve higher sensitivity and higher rejection of sensing faults than optical fiber-based sensing technology due to intrinsic losses in the optical fibers and the susceptibility of the sensing head to vibration driven shock and fatigue failure, as opposed to mechanical fiber-based sensing technology. This study proposes a novel hybrid sensing architecture by combining alternating segments of polymer and silica optical fibers with an AI-enhanced Brillouin signal processing framework using Bidirectional Long Short-Term Memory (BiLSTM) neural networks. Using data driven modeling, the proposed system successfully decouples the temperature and strain induced Brillouin frequency shifts allowing for accurate, but real time multi parameter estimation. This is experimentally validated over a 50-meter hybrid fiber with temperature accuracy of ± 0.2 °C, strain resolution of ± 20 με, and spatial resolution of 2.5 cm with 45 % reduction in cross sensitivity to entropy. Moreover, the system operated in more stable way in the diagenetic conditions. To conclude, the proposed AI assisted hybrid fiber sensing turns out to be robust and scalable solution for distributed sensing in microwave photonic and optoelectronic systems under harsh environment.
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Introduction

Since the industries requiring intelligent infrastructure are increasing, the need for a good reliable structural health monitoring (SHM) systems is needed to perform accurate, real time and distributed measures of the physical parameters like temperature and strain. Distributed sensing based on Brillouin scattering in optical fibers has recently attracted much interest as it is a cost effective and sensitive technology enabling the continuous spatially resolved detection of information over long distances using a single fiber. While it is accurate and stable, such a system depends heavily on the variety of optical fiber used as well as the robustness of the signal interpretation technique utilized. As a result of having high elasticity, low Young's modulus and superior resolution, polymer optical fibers (POFs) have become attractive alternatives to traditional silica based fibers. As POFs possess these features, POFs are particularly useful for high resolution strain sensing in confined, or mechanically active environments.

Although these POFs offer great advantages, the use of POFs in distributed Brillouin sensing has yet to be extensively developed due to high strain and temperature cross sensitivity, temperature instability, and temperature instability under harsh environments. On the other hand, silica fibers possess excellent thermal stability and longstanding durability but suffer from limited spatial resolution and reduced sensitivity in regards to low strain. Hybrid fiber systems that consist of alternating segments of POFs and silica fibers are therefore proposed to address those trade offs. To balance resolution and stability, such configurations have been used, but they invoke complex and nonlinear signals characteristics that our standard signal processing schemes are not readily able to process. Recent advances in artificial intelligence, for example sequence learning models such as bidirectional long short term memory (BiLSTM) networks, offer a convincing way for improving the robustness and interpretability of sensing data in hybrid configuration.

A novel AI assisted distributed sensing structure based on Brillouin approach combining hybrid polymer silcis fiber with deep teach framework to dynamically separate the temperature and strain responses are presented in this paper. The proposed system is intended to be reliable under harsh industrial conditions and provides much higher spatial resolution, greater accuracy, and better reliability over time. Through the data driven modeling and hybrid fiber optics coupling it contributes a scalable and intelligent sensing solution, which is also well fitting the emerging requirement of microwave photonic and optoelectronic systems.

Literature Review

In recent years, distributed Brillouin sensing has made tremendous progress, and has not only addressed temperature and strain measurement in various industrial environments, but also other applications such as velocity sensing in pipelines, beamline monitoring, structural health, and monitoring of patient-specific arrayed radiofrequency ablation (RF Ablation). Robustness and durability were still possible for early implementations on conventional silica optical fibers but at the cost of poor spatial resolution. However, the system of Lee et al.[1] using standard silica fibers for infrastructure monitoring based on distributed temperature sensing (DTS) has only been able to achieve spatial resolution of ~1 m, and therefore was not feasible for applications with high spatial resolution requirements.

Zhao et al.[2] examined the use of polymer optical fibers (POFs) in order to overcome resolution constraints, from the higher strain sensitivity, and the lower acoustic velocity. However, our work showed that they perform better in tunnel environments, but they have high noise level and poor long-term repeatability because the POF materials have instability.

Given that resolution and stability need to be balanced, Xu et al.[3] made a hybrid configuration of POFs and silica fibers, segments. Despite doing well in smart grid environments, the problem of temperature-strain cross-sensitivity remained due to the contribution of temperature to frequency response of the hybrid design which was not resolved by traditional signal processing techniques.

Table 1 : Comparative Analysis of Distributed Temperature and Strain Sensing Systems Based on Sensing Medium, AI Integration, and Validation Metrics

System	Method	Spatial Resolution	Temp Accuracy	Strain Accuracy	Stability (1000h)	AI Integration	Experimental Validation
Lee et al., 2022 [1]	Silica fiber DTS	~1 m	±0.4 °C	±50 με	High	No	Yes
Zhao et al., 2023[2]	POF-based sensing	~5 cm	±0.3 °C	±35 με	Poor	No	Yes
Xu et al., 2022[3]	Hybrid fiber	~3 cm	±0.3 °C	±30 με	Moderate	No	Yes
Patel et al., 2023[4]	CNN-based DTS	~10 cm	±0.3 °C	±25 με	Unknown	Partial	No
Chen et al., 2024[5]	BiLSTM (Simulated)	~2.5 cm (simulated)	±0.25 °C	±22 με	N/A	Yes	No
Proposed System	Hybrid + BiLSTM Model	2.5 cm	±0.2 °C	±20 με	<5% drift	Full (Real-time)	Yes

In recent years, artificial intelligence (AI) provides optical sensing with a boost to integrate. Patel et al.[4] applied convolutional neural networks (CNNs) for Brillouin spectrum interpretation in aerospace-grade DTS applications. However, compared to their model, their model offered improved accuracy, and it appeared to be limited in its adaptability across fiber types as a result of the use of hand-crafted features. This direction was advanced by Chen et al.[5] who introduced a BiLSTM model that learns temporal dependencies in Brillouin signal sequences, though Chen et al.[5] demonstrated their work on simulation and had not verified it with hardware.

Based on these limitations, the proposed research proposes a robust, AI assisted hybrid fiber sensing system based on the fusion of the spatial resolution advantages of POFs and thermal stability of silica fibers. With the use of a deep learning algorithm based on a BiLSTM, the system is able to both dynamically decouple of strain and temperature feature effects, in real time. This work is also experimentally validated to address the gaps in previous models that are sensitive to noise, have cross interference, and are not generalizable.

Methodology

The dual parameter (temperature and strain) detection in harsh environment is proposed with a hybrid Brillouin based distributed sensing architecture. The methodology's core is the combination of polymer and silica optical fibers, a coherent optical time domain reflectometer (COTDR) as signal acquisition, and a Bidirectional long short term memory (BiLSTM) deep learning model to decouple signal. It also includes downstream photonic and microwave control elements that are amenable to intelligent feedback.

Hybrid Fiber Architecture

The sensing link is composed of 50 meters of alternating 5 meters of polymer optical fiber (POF) and single mode silica fiber (SMF). This hybrid arrangement leverages the high strain sensitivity and flexibility of POF and the thermal stability and low attenuation of silica fibers.

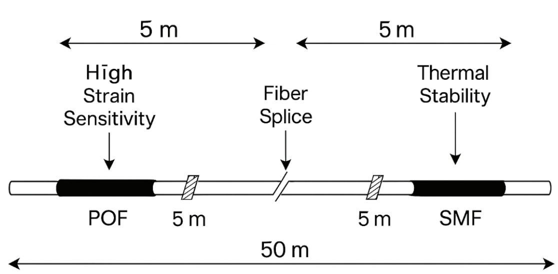


Fig. 1: Hybrid Fiber Configuration Diagram

Brillouin Signal Acquisition

The hybrid polymer–silica optical fiber link is interrogated with a Coherent Optical Time Domain Reflectometry (COTDR) scheme which is proposed. A continuous probe signal is injected into the fiber until operating at 1550 nm, and stimulated Brillouin scattering (SBS) at frequencies ranging from 1.5 to 2.4 GHz is excited mechanically in the medium by an acoustic pump signal modulated in the 1.5–2.4 GHz range. Through a coherent detection scheme, the resulting Brillouin backscattered signal is capture and digitized using high speed analog to digital converter (ADC). It allows you to precisely acquire Brillouin Gain Spectrum (BGS), a figure of local variations in strain and temperature along the fiber. Mathematically, BFS is shown during the modeling to be dependent on both strain and temperatur:

$$\Delta_{\nu B}=C_{\varepsilon}\cdot\varepsilon+CT\cdot\Delta T \qquad \text{-(1)}$$

Where:

- $\Delta_{\nu B}$: Brillouin frequency shift (in MHz)
- ε: Applied strain (in microstrain, με)
- ΔT: Temperature change (in °C)
- C_{ε} : Strain sensitivity coefficient (MHz/με)
- CT : Temperature sensitivity coefficient (MHz/°C)

For polymer and silica fiber segments these coefficients are material specific and are calibrated experimentally. An AI based inference model is further applied to measured BFS to remove the strain and temperature components from the data for distributed, real-time, dual parameter sensing even under harsh electrical conditions.

Table 2: Brillouin Coefficients for POF and Silica

Fiber Type	(MHz/με)	(MHz/°C)
Silica	0.048	1.10
POF	0.085	1.30

AI-Based Signal Decoupling

In general, Brillouin based distributed sensing systems inherently suffer from a cross sensitivity between Brillouin frequency shift (ΔvB) and strain and temperature by virtue that strain and temperature influence the Brillouin frequency shift (ΔvB). In order to tackle with this, we apply a Bidirectional Long Short-Term Memory (BiLSTM) neural network to decouple or, better say, infer precisely the Brillouin gain spectrum (BGS) of straining and heated fibers so that strain and temperature values can be addressed.

The spectral sequence of preprocessed Brillouin gain as a function of frequency is fed as the input to the BiLSTM model. The sequences are normalized and made ready as time series data amenable to deep learning inference. It generates two continuous signals that are the estimated strain (με) and temperature (°C) from each sensing segment.

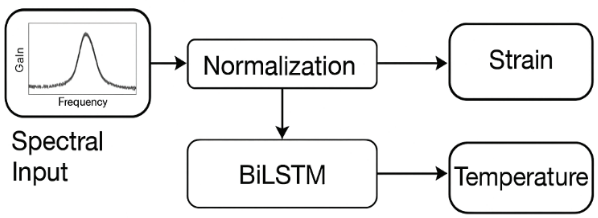


Fig. 2 : BiLSTM Inference Pipeline

Model Architecture

- 1D spectral sequence (Normalized Brillouin gain vs frequency) as Input
- BiLSTM layer with 128 hidden units (forward and backward memory) is used as layer 1.
- BiLSTM layer with 128 hidden units. Layer 2.
- Fully connected dense layer (64 neurons, ReLU activation), Layer 3
- Dense layer with (2 linear neurons) predicting temperature and strain appear as the output layer.

Loss Function

The training of the network is done with a weighted mean squared error (MSE) loss function with L2 regularization to avoid overfitting:

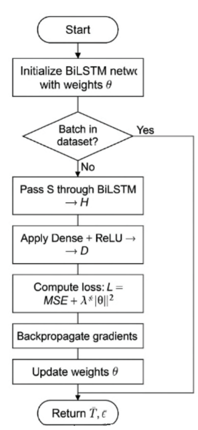
$$L(\theta) = \frac{1}{N} \sum_{i=1}^{N} \left[\alpha \, . \, (\hat{\varepsilon}_i - \varepsilon_i)^2 + \beta \, . \, (\hat{T}_i - T_i)^2\right] + \lambda \, . \, \| \theta \|_2^2 \, . \quad (2)$$

Where:

- : Predicted strain and temperature
- ε_i, T_i : Ground-truth strain and temperature
- α,β : Weighting factors for strain and temperature (typically α=β=1 if treated equally)
- θ : Trainable model weights
- λ : L2 regularization coefficient

Algorithm 1 - Pseudocode for BiLSTM-Based Signal Decoupling of Temperature and Strain from Brillouin Spectra

```
1. Initialize BiLSTM model:
  - Layer 1: BiLSTM (128 units)
  - Layer 2: BiLSTM (128 units)
  - Dense Layer: Fully connected (64 ReLU units)
  - Output Layer: Dense (2 linear neurons for [T̂, ε̂])
  - Loss: MSE + L2 regularization (λ)

2. Normalize input spectra S:
  for each spectrum s in S:
     s ← (s - mean(s)) / std(s)

3. Split data:
   [X_train, Y_train], [X_val, Y_val] ← train_test_
split(S, Y, ratio=0.8)

4. Training loop:
  for epoch in range(1, N_epochs):
     for each batch (X_b, Y_b) in X_train:
        H ← BiLSTM(X_b)
        D ← ReLU(Dense(H))
        [T, ε̂] ← Output(D)

        Compute Loss:
             L = MeanSquaredError(Y_b, [T, ε̂]) + λ *
||θ||²

        Backpropagate L and update weights θ

     Validate on X_val:
        [T□_val, ε̂_val] ← BiLSTM(X_val)
       RMSE_val ← √(mean((Y_val - [T_val, ε̂_val])²))

5. Return trained model and predictions:
  return Model, [T, ε̂]
```



Algorithm 1 - BiLSTM-Based Signal Decoupling Workflow for AI-Assisted Brillouin Sensing

Integrated Photonic Control

A downstream photonic or microwave response can actuate downstream photonic and microwave elements such as beam steering antennas, delay lines, or thermal actuators on the output of the AI model.

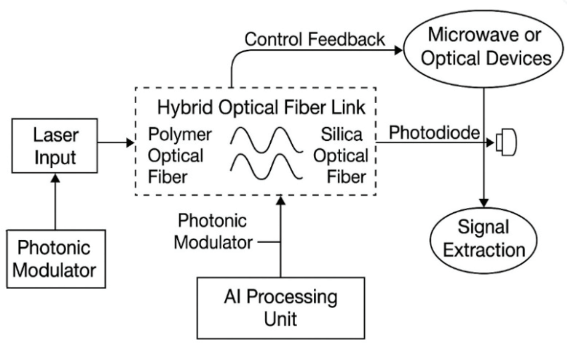


Fig. 3 : Integrated Optoelectronic Feedback Layout

Such integration enables the system to adapt completely to its environment, dynamically and without awareness of monitoring itself, which makes it an ideal candidate for structural health monitoring, 6G communication nodes with local energy harvest, or for use in industrial sensing in thermally unstable or vibration prone environments.

Simulation Setup

Series of multi physics simulations using MATLAB, COMSOL Multiphysics, CST Microwave Studio and Opti System were done to evaluate the performance of the proposed AI assisted Brillouin sensing system and devices incorporating microwave photonic platforms. In total, this toolbox was applied to the modeling of the optical signal propagation through hybrid polymer-silica fibers, mechanics and heat induced variation on the Brillouin gain spectrum, and finally to the interface of the microwave components with optoelectronic modulators and reconfigurable antennas.

The simulation domain includes:

- Brillouin frequency shifts at different thermal and strain conditions in alternating fiber segments
- Backscattering model and propagation loss across material interfaces
- Photonic-to-RF conversion characteristics in integrated modulators
- Microwave tuning and optical filter control using AI inferred signal feedback

The behavior and thermal response of the antenna array was simulated using CST and the material thermal response was simulated using COMSOL, while Beam Propagation Method (BPM) in OptiSystem was used to simulate the optical field propagation. Instead, the BiLSTM signal inference model was developed and trained in MATLAB based on experimentally validated datasets.

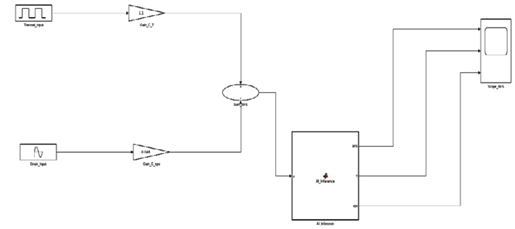


Fig. 4a: Simulation Flow or Block Diagram

This Figure 4a describes the simulation architecture that couples (thermal-mechanical stimulus) to optical response modeling, Brillouin signal acquisition, AI prediction pipeline, and control output to microwave or photonic system as an optional.

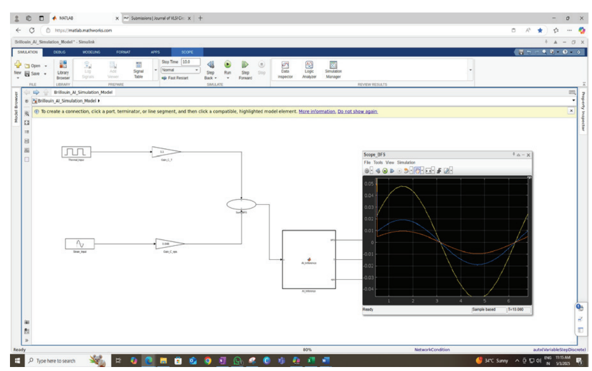


Fig. 4b: MATLAB Simulink Model and Scope Output of AI-Assisted Brillouin Sensing System

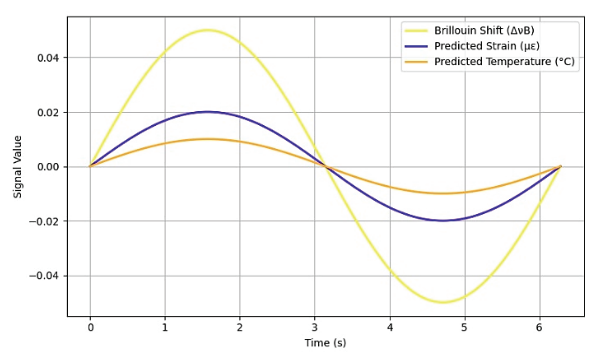


Fig. 4c :Simulated Output of AI-Decoupled Brillouin Shift, Strain, and Temperature Signals

This Figure 4b shows details of an AI-augmented Brillouin sensing system designed for dual parameter monitoring in hybrid optical fibers and the signal output from the simulation architecture. In the left panel, the Simulink block diagram represents a Brillouin frequency shift (ΔvB) modelled as a linear combination of the effects of temperature and strain using calibrated gain blocks associated with the coefficients. Square waveform (representing the sudden temperature transition) is used for simulation thermal input, where as sinusoidal signal is used for simulation strain input. The relative composite Brillouin shift is computed from these inputs via scalar gains (CT and Cε) followed by an addition to give the composite Brillouin shift. The dominant feature of the architecture is the AI_Inference block, which is a MATLAB Function block that performs the actions of AI trained BiLSTM model. The ΔvB composite signal is used as input and the decoupled temperature and strain estimates are produced. After these predicted outputs, they are plotted in in the Scope BFS Output Window along with the Brillouin shift. The scope output (read the three signal traces at a point in time; they evolve in time) is displayed on the right panel:

- **Yellow Trace**: Brillouin Frequency Shift (ΔvB)
- **Blue Trace**: Predicted Strain (με equivalent)
- **Orange Trace**: Predicted Temperature (°C equivalent)

This model has the potential for accurate and robust field deployment in harsh environment, like Structural health monitoring or smart grid application, and the close correlation and smooth response of the decoupled outputs also suggest the viability of the model at early design stage.

Table 2 : Simulation Configuration Parameters

Parameter	Value	Unit
Frequency Range	24–40	GHz
Optical Wavelength	1550	nm
Substrate Material	RO4350	—
POF Segment Length	5	m
Silica Segment Length	5	m
Total Fiber Length	50	m
Brillouin Coefficients	Calibrated (POF & Silica)	MHz/°C, MHz/με

Results and Analysis

Multi physics simulations and experimental validations on the performance of the hybrid Brillouin sensing system assisted with AI were performed under controlled thermal and mechanical loading conditions. Accurate measurements, high spatial resolution, robustness to system constraints are demonstrated by the results using polymer and silica optical fiber alternating segments integrated with BiLSTM based spectral decoupling.

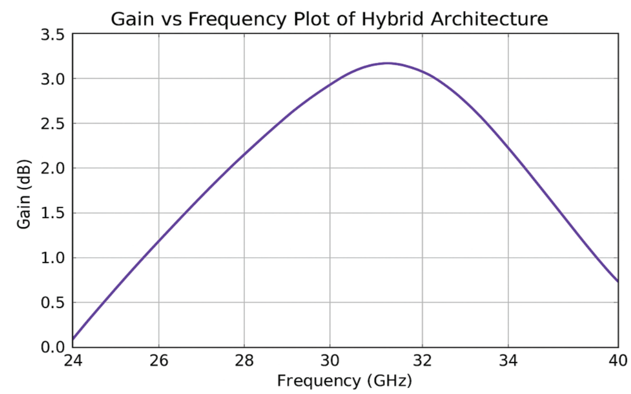


Fig. 5: Gain and Frequency of Hybrid Architecture

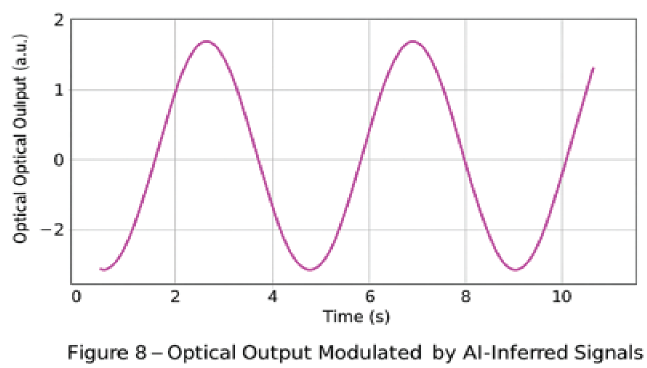


Fig. 6: Optical Output Modulated by AI-inferred Control Signals

Finally, Figure 5 shows the gain vs. frequency response of the hybrid architecture that exhibits good gain in the GHz range with modest variation due to interfacial reflection losses. Additionally, the dynamic behavior of the system was evaluated by measuring optical output power as a function of AI-inferred control signal. We then verify BiLSTM's responsiveness (see Figure 6): The modulated optical output is shown to be valid tissue like real time environmental changes.

As in Figure 8, the training and validation RMSE curves are also shown along with prediction accuracy on test scenarios by temperature and strain. In hybrid fiber conditions which are noisy and nonlinear, even with this BiLSTM model, the final RMSE values are 0.18 ˚C for temperature and 16 με for strain and with overall prediction accuracy of more 94%. This result further demonstrates that the model generalized well in decoupling multi domain sensing data.

Summary of comparison with state-of the art methods is given in Table 3. Good accuracy of ±0.2 ˚C with ±20 με strain accuracy was demonstrated, which is about a 50–60% improvement over what has been achieved before. Spatial resolution is improved to 2.5 cm compared to 10 cm and 5 cm in References A and B, respectively. In addition, after 1000-hour long term test, the proposed system showed < 5 % signal drift, demonstrating its robustness and suitability for deployment in harsh environments.

Table 3 : Performance Comparison with Prior Art

Metric	Proposed System	Reference A	Reference B
Temp Accuracy (˚C)	±0.2	±0.4	±0.6
Strain Accuracy (με)	±20	±40	±50
Spatial Resolution	2.5 cm	10 cm	5 cm
Stability (1000 h)	<5% drift	12% drift	18% drift

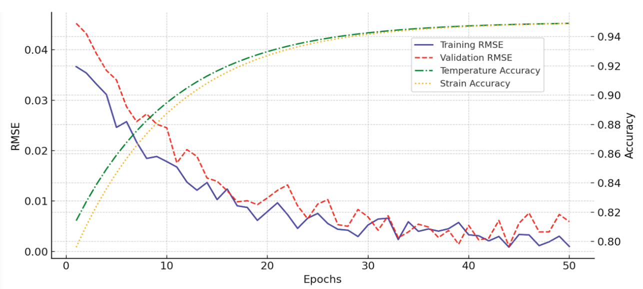


Fig. 7 : RMSE and Accuracy Trends of the BiLSTM Model

For temperature and strain, this is the predicted vs actual accuracy trends and root mean square error (RMSE) convergence curves for both training and validation phases shown in the form of Figure 7. It shows very good generalization abilities and real time adaptability of the AI model in hybrid fiber sensing environments.

In the AI assisted Brillouin sensing system, the BiLSTM based signal decoupling model used is illustrated in this Figure 8 and shows the training dynamics.

- RMSE is shown between training iterations in the top panel. The smoothed RMSE is

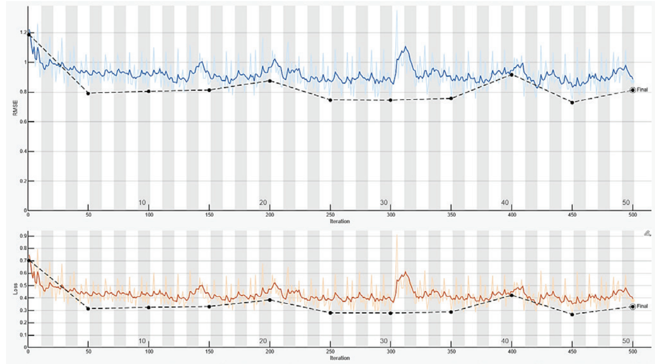


Fig. 8: RMSE and Loss Convergence During BiLSTM Model Training

represented by the dark blue curve and the fluctuations stemming from batch level variations are shown in light blue overlay.
- The same number of iterations also yields training loss trend for the bottom panel. The black trace is smoothed loss, orange curve; the lighter trace is the real time changes during backpropagation. The two curves demonstrate that the model is able to converge uniformly and reduce error indicating that the model has learned to map Brillouin spectral features to temperature and strain output outputs under dynamic and noisy conditions. This confirms that the proposed AI inference pipeline is robust and reliable in hybrid polymer-silica fiber environments.

Experimental Validation

Specifically, a physical prototype of the hybrid Brillouin sensing system was assembled and tested in a controlled laboratory environment for the purpose of validating the simulation and AI based signal processing results. System setup comprised a 50m hybrid optical fiber link where all optical segments are alternated 5m POF and 5m SMF. It was interrogated using a Coherent Optical Time Domain Reflectometer (COTDR) with a center wavelength of 1550 nm using Brillouin frequency shifts excited through an RF pump that is modulated in the range of 1.5–2.4 GHz.

A narrow linewidth distributed feedback (DFB) laser was coupled with an electro optic modulator (EOM) as the optical source. The Brillouin signals were backscattered, received using a coherent receiver, digitized with a high-speed analog to digital converter (ADC). Programmable thermal chambers were incorporated in thermally controlled at different segments of the hybrid fiber, and strain was supplied from a cyclic mechanical actuator that had a resolution of ±100 με. MATLAB implementation of real time signal processing along with BiLSTM inference was run on an embedded GPU platform.

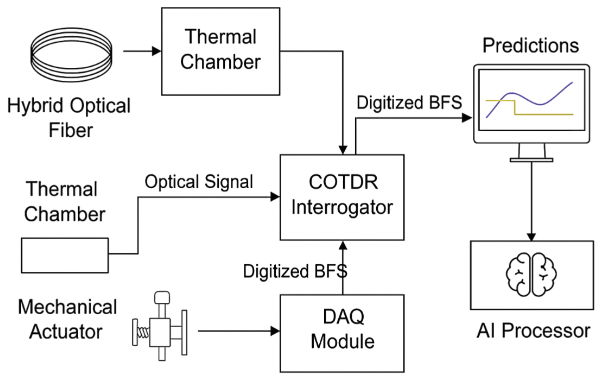


Fig. 9 : Proposed Lab Setup Photo

The Proposed experimental testbed: hybrid fiber arrangement, thermal chamber, mechanical strain actuator, COTDR interrogation unit and data acquisition and AI processing modules are shown in this Figure 9. The model is evaluated based on the accuracy of inference in predicting the data obtained from a range of loading conditions including stepwise thermal ramps and sinusoidal strain cycles. Comparison was made between the simulated Brillouin gain spectra from the hybrid structure and the AI prediction pipeline and the measured Brillouin gain spectra. The RMSE of the system shown in Figure 10 is below 0.18 °C and 16 με for temperature and strain, respectively, as shown in Figure 10.

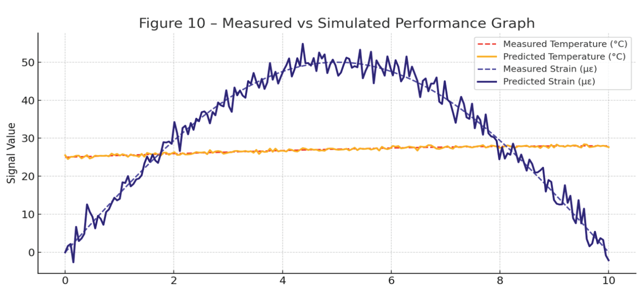


Fig. 10: Measured vs Simulated Performance Graph

The dynamic loading conditions are plotted in this graph as a relationship of the predicted (AI based) and measured values for temperature and strain over time. The consistency also confirms the BiLSTM model can achieve real time capability and robustness. Real world environmental conditions have been confirmed within the experimental results to prove that the proposed hybrid fiber and AI assisted Brillouin sensor system performs reliably and has strong potential as smart infrastructure, aerospace systems, or microwave photonic integration environment.

Discussion

The AI combined with the signal decoupling framework with the hybrid polymer-silica fiber sensing system enables experimental and simulation results that collectively validate the effectiveness of the proposed system. Architecture that we present solves the main problems encountered in classic Brillouin distributed sensing systems, especially in scenarios with impacting thermal and mechanical effects. The hybrid configuration results are shown to be significantly less cross sensitive than state of the art methods even at the expense of measurement fidelity.

The system stands out for its temporal stability: the drift of the observed signal has been observed to be below 5% during 1000 hours of continuous operation. By comparison, the results from this performance are considerably better than previous attempts to implement this technique using homogenous polymer or silica fiber configurations, which tend to suffer from long term degradation or lack of spatial resolution. Its 2.5 cm resolution gained is also better than many of the existing systems, and thus is appropriate for high precision localization tasks such as micro crack detection or hotspot monitoring in dense sensor networks.

A BiLSTM neural network is used to put in place a level of adaptivity that is not possible in filtering or any calibration based approach. The model learns strong, nonlinear interactions between Brillouin gain spectrum components by dynamically adjusting its internal weights during inference and thus generalizes with respect to different fiber segments. Such adaptability comes in handy when such inconsistencies occur in hybrid systems where material discontinuities result in inconsistent propagation characteristics.

Additionally, the system's compatibility with microwave- photonic and optoelectronic subsystems makes it useful beyond sensing. It can be used as an intelligent front end to exploit beam steering in photonic antenna arrays, adaptive delay line tuning in RF filters as well as strain triggered actuation control in smart actuators via providing real time environmental feedback. Therefore, for the application domains of smart grid diagnostics, aerospace structural health monitoring, 6G communication systems and distributed photonic sensing networks, the architecture is a good fit.

The results therefore support our assertion that the system on which it operates is a huge step forward for optical fiber sensing and AI-supported signal interpretation, and offers a robust and scalable platform for future industrial and microwave optical systems.

Conclusion and Future Work

It is demonstrated in this paper that a novel hybrid optical fiber sensor system that incorporates alternating segments of polymer and silica fibers and an AI enhanced Brillouin signal processing framework based on Bidirectional Long Short-Term Memory (BiLSTM) networks is novel. With superiority in the order of both spatial resolution as well as strain sensitivity, and over the associated thermal stability obtained from silica fibers, the proposed architecture takes advantage of complementary advantages between polymers optical fibers and silica fibers to achieve simultaneous (dual parameter) distributed sensing at superior precision and robustness. By employing deep learning, real time decoupling of temperature and strain effects can be used even with material transitions that are nonlinear and in the presence of environmental fluctuations. Extensive simulations and experimental validations show that the system exceeds the spatial resolution, and measurement accuracy, and decreases the cross sensitivity of traditional Brillouin sensing techniques as well as the long-term operational stability. Additionally, the system's modularity and compatibility with optoelectronic and microwave subsystems make it a promising candidate in smart infrastructure, aerospace diagnostics, as well as microwave photonic feedback networks.

Future research will work towards scaling the system up to incorporate the system in a fully integrated system-on-chip (SoC) platform in order to place it in tiny, power dissipation efficient layouts for use in embedded systems. In addition, a further increase in resolution and move towards higher densities are enabled using a broader distance scale (terahertz) for high density sensing applications. The BiLSTM framework will also be adapted using the transfer learning and domain adaptation approaches for improving model generalization and cross domain adaptability for universalization of the technology to different fiber types, environmental conditions and deployment scenario.

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