Propagation of uncertainty in data-driven models used for long-period fiber grating interrogation

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***Abstract*—The use of machine learning (ML) for processing fiber optic sensors (FOS) signals has several advantages. Some ML models have great data abstraction capability, thus allowing data interpolation and/or extrapolation. Thus, it enables the interrogation of long-period fiber grating (LPFG) sensors using a sparse filter array. In this case, an array of optical powers filtered by the filter array is processed by the ML model to estimate the LPFG resonance. This setup provides great scalability, because it is sensor-independent, i.e., there is no need for the interrogator to be calibrated for each LPFG. In this work we present a study on the uncertainty propagation in such interrogation scheme.**

Keywords*—*fuzzy inference system, neural networks, error statistics, model validation, sensor interrogation, signal conditioning

I. Introduction

In recent years, applied machine learning has increased, particularly in the field of sensors [1]–[3]. For fiber-optic sensors (FOS) this trend was not different [4], [5]. The signal conditioning of FOS is often called interrogation, and it involves the measurement of light characteristics, such as wavelength. The fiber gratings are notable examples of wavelength-encoded transducers, both the fiber Bragg gratings (FBGs) and the long-period fiber gratings (LPFGs). For LPFGs, however, the interrogation is often more demanding, because of its spectrum. While in FBGs, the Bragg wavelength is the desired parameter and it is well-defined as the center of a resonant peak, in LPFGs the optical spectrum is much more complex. Instead of a single peak, the LPFG spectrum is characterized by several rejection bands, each one due to a resonant wavelength, λ_{res} . Therefore, the whole spectrum measurement is used in most applications.

Several works have focused on the development of simpler forms of grating-based FOS interrogation. Note that, the main parameters often needed for sensor calibration is a single wavelength, which represents the FBG's peak or the LPFG's dip. Thus, the use of complex optoelectronics to acquire the sensor spectrum might be inefficient in certain cases.

Some recent approaches focus on single (or sparse) acquisition of optical power, i.e., the use of one (or more) optical filter and the detection of the filtered optical power. One method is based on the use of an arrayed waveguide grating (AWG) to filter the sensor spectrum and estimate the desired parameter. Due to the AWG channel spacing, the FBG peak can be easily estimated by neighboring channels at the FBG vicinity [6], with possibility to improve the cost-effectiveness when coupled to a smart channel-selecting system assisted by deep learning [7]. Note that an FBG peak width is as low as a fraction of a nanometer, whereas an LPFG dip might be as wide as tenths of nanometers. Therefore, the channel density of AWGs can be used for whole spectrum estimation for LPFG [8].

However, other methods rely on edge filtering, with limited number of filters. To estimate an FBG position, for example, an LPFG could be used as edge filter [9], or other FBGs close to the sensing FBG [10]. Similarly, to interrogate LPFGs, one could use one or more FBGs as edge filters [11], or a sparse filter bank [12].

In this work we study the uncertainty propagation through machine learning models used to interrogate LPFG-based sensors. The method for λ_{res} estimation can be seen in Fig. 1. Note that, the use of ML models for FOS signal conditioning is widely adopted [13]–[15], but the literature lacks a comprehensive analysis of uncertainty propagation through the ML models applied to FOS signal processing. So, here we revisit the models and dataset presented in [12], to preset a study on the uncertainty and its propagation through the interrogator signal conditioning ML model.

II. Methods

The uncertainty in M L models is divided into two types: epistemic and aleatoric [16]. They are, respectively, due to the model uncertainty and event uncertainty. They are similar to the systematic and aleatoric error found in measurements.

The models considered in this work were: linear regression model, multilayer perceptron (MLP), two fuzzy inference systems (FIS) – one manually set and other optimized by

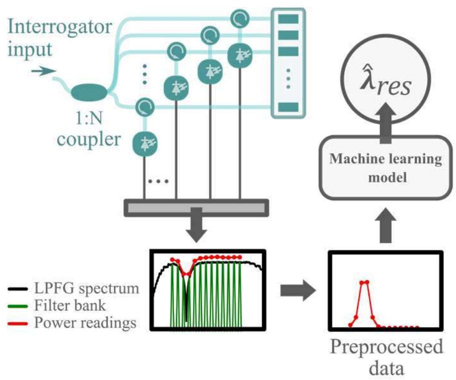

Fig. 1 – Schematic of the ML-assisted LPFG interrogator.

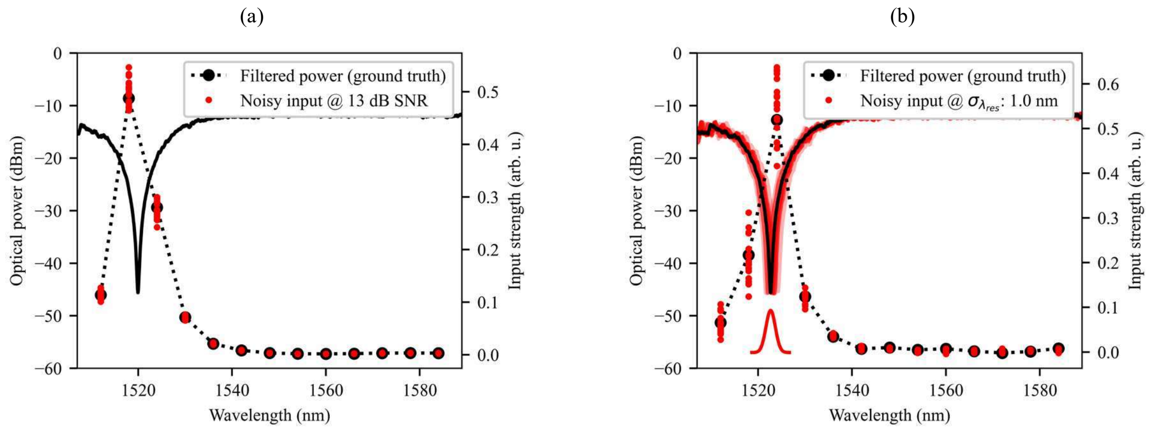

Fig. 2 – Example of uncertainties at the interrogator input: (a) uncertainty due to optoelectronic noise and (b) uncertainty due to LPFG sensor fluctuation.

genetic algorithm [12]. All of them were trained (calibrated) as discussed in [12]. The hardware used to collect the models' input data was a 13 FBG sparse filter bank. An overview of the system can be seen in Fig. 1.

In this work, we evaluate the aleatoric uncertainty only. Note that the models considered in this work are simple and we considered that they were properly trained with a training set that represents well all the input data space, so epistemic uncertainty is negligible.

We consider the model's input as the main source of uncertainty. However, the input change due to the LPFG position and to the interrogator's optoelectronics. So, we used semi-synthetic data to evaluate the model. We used additive gaussian noise (AWGN) to the FBG-filtered power, to model the optoelectronic noise, and gaussian distributed LPFG spectrum shifts, to model the LPFG position's uncertainty.

Fig. 2 shows the results of such simulations on an LPFG spectrum, the black parameters are static (ground truth), whereas the red values show the noise added during the Monte Carlo simulations. Fig. 2a. shows the effect of slight deviations in the LPFG position and Fig. 2b shows the effect of optoelectronic noise.

We simulated 20 random samples for each of the 159 spectra obtained from 83 different LPFGs (dataset used in [12]), and compared the interrogator's output to the desired value, obtaining the residues $r = \lambda_{res} - \hat{\lambda}_{res}$. This process was repeated 10 times for each input uncertainty and the residue statistics was evaluated to study the uncertainty propagation.

III. Results

First, let us study the effects of optoelectronic noise, i.e., the input fluctuations when the LPFG sensor is static and the filtered power fluctuates. Fig. 3 shows the residue bias as a function of u_a. Note that, generally, the bias doesn't present a clear trend with respect to the SNR, except for the Linear model under high noise, but with great variability among our tests. The standard deviation, on the other hand, shows a clear increasing trend correlated to the input noise, see Fig. 4, where the curves show the uncertainty propagation due to the input SNR. Based on such results, we were able to infer that the input noise doesn't affect the bias of ML-based models tested in this work.

However, note that the high noise insensitivity of the models might rise concerns regarding the LPFG sensor fluctuation. Indeed, because the models lessen variations in the FBG's filtered power, consequently, the models might not transfer all LPFG fluctuations to $\hat{\lambda}_{res}$ In other words, the noise robustness might result in loss of interrogator resolution.

Fig. 5 shows the bias as a function of LPFG fluctuation. The results show the bias also doesn't correlate to the input fluctuation. Thus, we calculated the typical bias range for fluctuating LPFGs: 0.028 ~ 0.030 nm for the Linear model, 0.081 ~ 0.083 nm for the MLP, 0.120 ~ 0.122 nm for the FIS-ex, and 0.099 ~ 0.101 nm for the FIS-ga. These values illustrate the stability of the proposed interrogator since they are in accordance with the results obtained in [12] and provide a glimpse on the models' epistemic uncertainty.

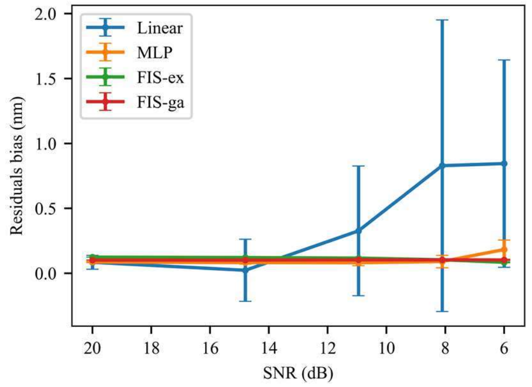

Fig. 3 – Bias due to input power SNR.

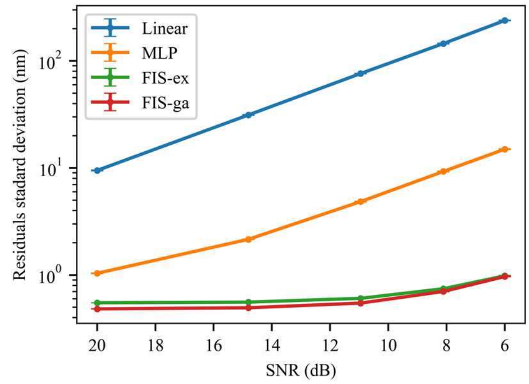

Fig. 4 – Standard deviation due to input power SNR.

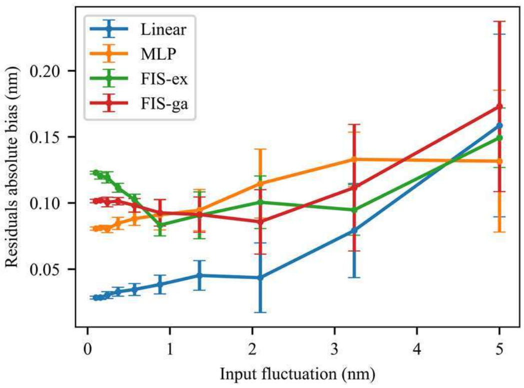

Fig. 5 – Bias due to LPFG sensor fluctuation.

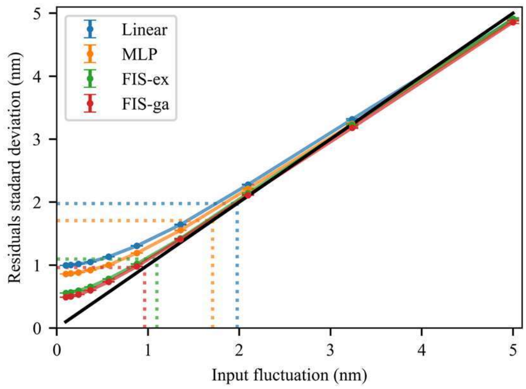

Fig. 6 – Standard deviation due to LPFG sensor fluctuation.

As for the residuals standard deviation, it is desired that all input fluctuations are passed through the model to the estimated resonant wavelength. So, ideally, a 1:1 ratio between u_b and the r standard deviation is desired. However, the measuring instruments presents a resolution, so not all minor fluctuations should be transferred to the interrogator's output. Indeed, the results showed that the residuals' standard deviation clips at a certain value, see Fig. 6.

IV. Conclusions

This work we studied the LPFG-based fiber optic sensor interrogation. A sparse filter bank with 13 FBGs was employed, and the focus was on evaluating the uncertainty propagation in the interrogator's signal processing chain. Results indicated the models used do not introduce systematic errors under uncertain scenarios due to stable residual bias.

Additionally, the FIS models exhibited a damping effect on optoelectronic noise, remaining insensitive to SNR within the 20 dB to 11 dB range. LPFG fluctuations were not impacted by this damping effect, as the standard deviation of residuals aligns with the input sensor's standard deviation. The methodology employed holds potential for developing equations that explains the uncertainty propagation in ML-assisted FOS instruments and interrogators.

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