Structural Health Monitoring of a Satellite Antenna: A Benchmark Between the Modal Method, iFEM Coupled with Modal Strain Expansion, and a Physics-Informed Neural Network

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ABSTRACT

Shape sensing techniques for real-time deformation reconstruction are an increasingly important topic for Structural Health Monitoring (SHM), particularly in the context of digitalisation and digital twins. Artificial intelligence and artificial neural networks are showing promising results for such tasks. Physics-Informed Neural Networks (PINN) have recently gained interest due to less training data-dependent predictions by incorporating physics laws into the training. To benchmark such a PINN for solving inverse problems in shape sensing, referred to as "iPINN", this paper presents a study on its performance against the Modal Method (MM) as an established technique on the example of a composite space antenna. Moreover, a combination of the two mainstream methods for shape sensing is tested on the same space structure. Starting from a few strain measurements, the strain field is first expanded using a variation of the MM. Then, displacements are reconstructed using the inverse Finite Element Method (iFEM). This study shows that both the iPINN and the combination of MM and iFEM can produce predictions of deformed shapes, although further investigations are needed to improve their accuracy.

INTRODUCTION

In recent years, Structural Health Monitoring (SHM) has gained growing interest across various fields where structural performance is critical. Applications such as bridges and aerospace components already benefit from SHM systems, which are employed to perform damage detection and monitoring to ensure safe operations [1, 2]. Besides, SHM systems enable shape and load sensing, providing real-time data on operational loads and deformations. These techniques not only offer early warnings of potential overloads [3] but also supply valuable data for design optimisation in future product generations [4, 5]. A key challenge in these applications is the accurate deformation and load field reconstruction, crucial for informed decision-making. This challenge becomes even more significant when few sensors are available, a condition where

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established shape sensing techniques often struggle to ensure high accuracy [6]. To overcome this limitation, neural networks, especially Physics-Informed Neural Networks (PINNs), have emerged as promising alternatives in the literature [7,8]. However, to the best of the authors' knowledge, a benchmark comparing such PINNs to established shape sensing techniques is currently lacking. This paper aims to fill this gap by evaluating the performance of a PINN for solving inverse problems in shape sensing (iPINN) against two approaches: the classical Modal Method (MM) and a novel hybrid approach that combines the MM with the inverse Finite Element Method (iFEM). For this purpose, the paper is structured as follows: Section 2 provides an overview of the shape sensing techniques applied in this paper. Building up on this, Section 3 presents the benchmark study, conducted on the boom of a satellite antenna for demonstration. Finally, Section 4 concludes this paper and outlines directions for future work.

SHAPE RECONSTRUCTION METHODS

In the current state of the art, various techniques, commonly called shape sensing techniques, have been developed to reconstruct deformed shapes from strain sensor measurements at discrete locations. These techniques can be clustered into the following four main groups: (1) methods based on the numerical integration of experimental strains; (2) methods using global or piecewise continuous basis functions to approximate the displacement field; (3) methods based on a Finite Element (FE) discrete variational principle and (4) methods employing Artificial Neural Networks (ANNs) [9].
The first group's primary representative is Ko's displacement theory [10], which allows the reconstruction of applied loads using the Euler-Bernoulli beam theory. However, it is mostly limited to slender, beam-like structures.
In the second group, the Modal Method (MM) is the most widely used technique. Originally presented by Foss and Haugse in 1995 [11], it estimates the displacement field $\mathbf{u}$ from the strain measurements $\boldsymbol{\varepsilon}$ at discrete locations using Equation (1).

$$\mathbf{u} = \boldsymbol{\phi}_d(\boldsymbol{\phi}_s^T\boldsymbol{\phi}_s)^{-1}\boldsymbol{\phi}_s^T\boldsymbol{\varepsilon} \tag{1}$$

The matrices $\boldsymbol{\phi}_d$ and $\boldsymbol{\phi}_s$ denote the modal shape matrices for the displacements and strains, respectively. As it is often impractical to obtain modal data experimentally, Finite Element Method (FEM)-based simulations are typically employed [6]. An important advantage of the MM is that it yields accurate results with few sensors. However, according to the literature, it is difficult to get the error in the displacement reconstruction to less than $\approx 5\,\%$, especially when local effects are present [12].
The third group of shape sensing techniques includes the inverse Finite Element Method (iFEM), developed by Tessler and Spangler in 2003 [13]. It received significant attention thanks to its ability to produce highly accurate results while being robust and material-independent. This technique discretises the structure with specific finite elements to compute the unknown nodal degrees of freedom by minimising a square error functional on the input strain measurements. The major drawback of iFEM is its requirement for many strain measurements to produce accurate results. Therefore, recent research has focused on reducing the number of required sensors. One work proposed new shell element formulations using strain measurements only on one side of the structure [14].

Another promising approach combines the MM and iFEM to exploit both methods' advantages. It is a two-step approach; first, the few strain measurements are expanded to a broader set using a variation of the MM called Modal Virtual Strain Expansion (MVSE). Then, the expanded strains are used as inputs for the iFEM, which performs the shape sensing [12].

In the fourth group, ANNs applications in shape sensing can be found in several studies on different structures. For instance, Bruno et al. [15] used a simple Fully-connected Neural Network (FNN) to predict the deformation field of a truss structure. A drawback of these ANNs is their dependence on the training datasets. This issue was addressed by Raissi et al. in 2019 [16] by introducing Physics-Informed Neural Networks (PINNs). This kind of ANN considers physics laws during the training process by learning to solve Partial Differential Equations (PDEs). For example, Qui et al. [7] developed a PINN for shape sensing, which is trained to predict the displacement field from strain measurements, where the strains are derived as PDEs from the predicted displacements during training. Additionally, boundary conditions can be applied in the training process, as presented by Go et al. [8]. Even though the PINNs in the applications show great potential to yield highly accurate deformation field predictions with errors $< 1\,\%$, there is still lack of information on the number of sensors required to achieve such performance.

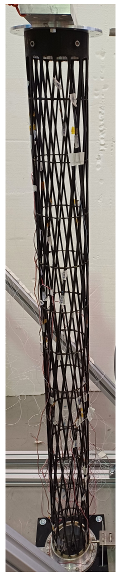
To help address this gap, this paper presents a benchmark study between three shape sensing methods: the MM as a well established technique, a hybrid approach combining the MVSE with iFEM and a iPINN-based method. The aim is to compare their performance, particularly with limited sensor availability.

CASE STUDY

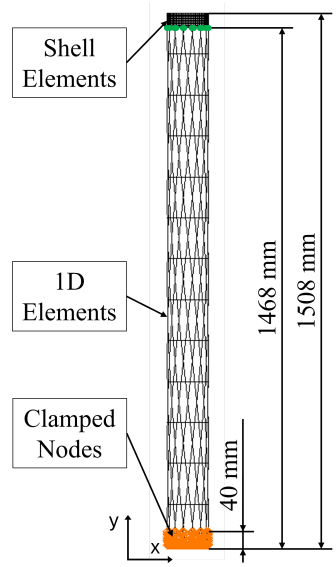
To benchmark the accuracy of a iPINN-based shape sensing method and of a hybrid method combining MVSE and iFEM, a case study is conducted on a satellite boom for large deployable reflectors (LR-BOOM). This structure, described in more detail by Giusto et al. [17] and De Nicola et al. [18], is constructed from a Carbon Fibre Reinforced Polymer (CFRP) in a tubular grid architecture. The boom is manufactured by an automated winding technique, which allows the structural integration of strain sensors. For this study, 16 single linear strain gauges are used. This number was chosen because typical data acquisition systems support 4 or 8 channels per card, and 16 is often the upper limit for standard configurations. Figure 1 shows the LR-BOOM structure alongside its FE model used for this case study, which consists of one-dimensional (1D) and two-dimensional (2D) quadrilateral shell elements.

Modal Method

An Optimal Sensor Placement (OSP) is carried out to define optimal sensor locations for the shape sensing task of this study with the MM by using Matlab's built-in multi-objective genetic algorithm function *gamultobj()*. The natural modes used in this study are selected by using the strain energy criterion [11] and are eight in total. The optimisation considers two load cases: a transverse force and a torque. In both cases, the nodes in orange in Figure 1b have all six degrees of freedom, three displacements and three rotations, constrained. The loads are applied to a node located at the centre of the



(a) The physical structure



(b) The FE model

Figure 1. The structure of the LR-BOOM used in this study as a physical and a FE model.

tip section, which is connected to the 2D elements via rigid body elements. Two error parameters are considered for each load case: the normalised root mean squared error ($NRMSE$ in Eq. (2)), and the maximum relative error at the tip ($TipErr$ in Eq. (3)).

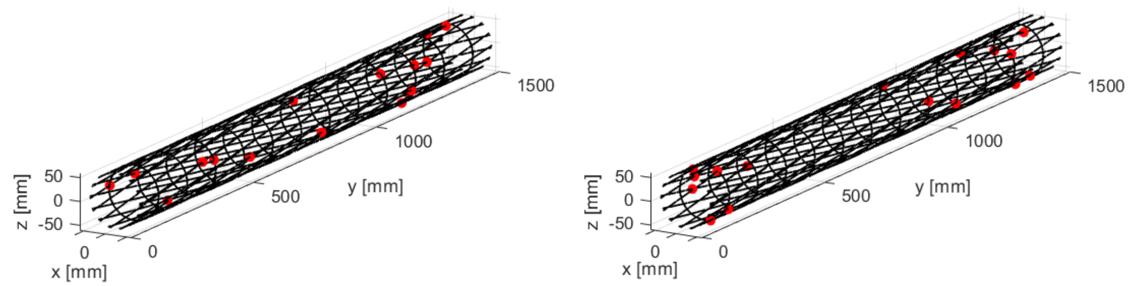
$$NRMSE = \frac{\sqrt{\frac{1}{n}\sum_i \sum_j \left(d_{i,j}^{Ref} - d_{i,j}^{SS}\right)^2}}{\max_{i,j} d_{i,j}^{Ref}} \tag{2}$$

$$TipErr = \frac{\max_{i,j} \left| d_{i,j}^{Ref} - d_{i,j}^{SS} \right|}{\max_{i,j} d_{i,j}^{Ref}} \tag{3}$$

Here, d is the displacement, Ref and SS refer to data coming from the reference FE model or the shape sensing process, respectively. The index $i = x, y, z$ represents the direction of the displacement. The index j represents the node for which the displacement is computed, and n is the number of nodes in the model. In the $NRMSE$ definition, $j = 1, 2, ..., n$, while in the $TipErr$ definition, j only includes the nodes part of both the beam and the shell elements at the loaded end (in green in Figure 1b). Therefore, a total of four error values were computed for each reconstruction, two per load case. The two $TipErr$s were used as fitness functions, while the two $NRMSE$s were imposed as non-linear constraints. The OSP is carried out with a threshold of $NRMSE = 5\,\%$, which was defined from a study where the values of $2\,\%$, $3\,\%$, $5\,\%$, and $10\,\%$ were tested in terms of computational efficiency and accuracy. The resulting sensor configuration is depicted in Figure 2a, where the red dots mark the 16 sensor locations.

MVSE and iFEM

Another OSP is carried out for shape sensing with the MVSE coupled with iFEM, a two-step method based on the work by Esposito [12]. During the optimisation, the



(a) For the MM and the iPINN

(b) For the MVSE with iFEM

Figure 2. Strain sensor placements resulting from the optimisations in this study.

sixteen input strain measurements are expanded to the entire set of strain measurement locations first using the MVSE, with the same natural modes as the MM. Then, the set of expanded, or virtual, strain measurements is used as the input for the iFEM, which outputs the full field displacements, performing the shape sensing. The setup of this optimization in terms of load cases, fitness function, and constraints is equivalent to the one presented for the MM, but the threshold for the $NRMSE$ is here set to $20\,\%$ to ensure feasible solutions. The resulting sensor configuration is depicted in Figure 2b.

iPINN

The iPINN used in this study is trained for shape sensing using strain data from the sensor positions resulting from the OSP for the MM. Its architecture is based on the study of [8], where the iPINN receives the coordinates of the collocation points, locations where displacement is reconstructed, as inputs in three separate input neurons (x, y and z coordinates). Additionally, the iPINN has an input neuron for each of the 16 sensors. This input contains the coordinates and the measured strain in the form $[x, y, z, \varepsilon]$, where ε is the measured strain along the longitudinal axis of the specific bar element. All inputs are then processed through a FNN, consisting of five hidden layers with 64 neurons each. The ReLU activation function is used, as its non-linearity enables the network to model complex relationships between input and output. A two-step training is performed with an initial phase using the Adam optimiser for 2000 epochs, then a refinement phase with the L-BFGS optimiser, as in [8]. This approach allows for better fine-tuning of neuron weights and better predictions than using only one of these two optimisations. A loss consisting of three terms is used to include physics laws in the training process. First, there is a general data loss, describing the deviation between predictions and reference data for the displacements at the collocation points. Then, there are two terms including physics knowledge in the training. One is for the boundary condition of the clamped end of the LR-BOOM (see Figure 1b) as Dirichlet Boundary loss [8]. The other is for the strain loss, computed as the deviation between the strain field from the FE simulation and the strains resulting from the derivation of the predicted displacements.
The iPINN training data is generated through FE simulations of the LR-BOOM, where each case involves a transverse force and a torque. A total of 100 training datasets

TABLE I. Comparison of error metrics for the three tested methods.

Method	NRMSE	TipErr
Modal Method	0.394 %	0.475 %
iPINN	6.673 %	15.828 %
MVSE with iFEM	13.178 %	20.457 %

were created by randomly varying the transverse force from a normal distribution with $\mu = 100\,N$ and $\sigma = 80\,N$ and computing the torque as $T = F * 0.5\,m$.

Results

All three methods are benchmarked against the validation load case not used for optimisation or training, which is combining different structural effects due to the transverse force $F = 100\,N$ and the torque $T = 50\,Nm$. To compare the accuracy of the three shape sensing methods, two error metrics are computed on the comparison load case using the $NRMSE$ and the $TipErr$ as described in Eqs. (2) and (3). The results are shown in Table I.

Among the evaluated techniques, the MM provides the highest accuracy, with significantly lower error values across both metrics. The iPINN outperforms the MVSE and iFEM combination, although both methods produce reconstruction errors which are generally too large for practical use. It is worth noting that the iPINN's sensor configuration was not specifically optimised for the approach, and the training is not performed with the error metrics used in the comparison. Furthermore, only a single architecture - an FNN with ReLu activation - was considered. The training dataset can also impact the iPINN's performance, despite integrating physics laws. Using randomly generated load cases from a normal distribution could introduce a bias affecting reconstruction accuracy. Regarding the MVSE with iFEM, the virtual sensors set was not optimized, only the real sensor one. Additionally, the inverse mesh for iFEM was also not optimized; the discretization was achieved by merging two adjacent FE mesh elements, which, being the finest possible with the available inputs, is typically not optimal for iFEM.

CONCLUSIONS AND FUTURE WORK

SHM is critical in various forms and applications, from damage detection to real-time structural monitoring. Within this field, shape sensing allows the reconstruction of full-field displacements from strain measurements at discrete locations. While established methods like the MM are widely used, they struggle to lower their error to less than $5\,\%$, especially when strong local phenomena are involved. In contrast, other established techniques, such as iFEM, struggle with limited strain sensor availability. PINNs for solving inverse problems, as in the case of shape sensing, have the promising ability to overcome these issues. However, their performance regarding limited strain input data has not been thoroughly investigated.

This work presents a benchmark study comparing an iPINN and a hybrid approach combining the MVSE with the iFEM, to reduce the sensors required for the iFEM, to the well-established MM. The benchmark is based on the example of a CFRP satellite an-

tenna boom, known as LR-BOOM. From the results, it becomes clear that the MM outperforms both alternative techniques in this setup. Among the two proposed methods, the iPINN results in more accurate predictions than the MVSE with iFEM approach.
Future research will further explore the iPINN used in this study to improve its shape sensing capabilities. Alternative ANN architectures, such as convolutional or graph neural networks, will be considered, along with different physics-based training constraints, to showcase various iPINNs. For example, including modal characteristics in the training may improve both accuracy and robustness [19]. The MVSE with iFEM approach also offers room for further improvements. A promising direction involves expanding the physical strain sensors only to selected locations rather than the entire field [12]. This selective expansion could help to improve the MVSE in capturing local phenomena under concentrated loads. Moreover, using a less refined inverse mesh typically improves the results of iFEM so this will also be investigated in future work. Both methods will also be tested on load cases where the MM struggles, to evaluate their potential as alternatives. Finally, assessing the robustness of these methods to sensor failure or measurement errors will be crucial, especially for future experimental applications.

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