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MACHINE LEARNING APPROACH FOR SENSOR PLACEMENT OPTIMIZATION

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Abstract

This paper presents a novel approach that combines deep learning techniques with traditional sensor placement optimization methods for modal identification of bridge structures. The proposed methodology is developed and validated using experimental data from three bridges instrumented with more than 20 sensors each. A Neural Network architecture is designed to learn optimal sensor configurations based on Modal Assurance Criterion (MAC) values, modal shapes, and natural frequencies. Comparisons with traditional optimization methods demonstrate improvements in both computational efficiency and placement quality. The proposed machine learning framework effectively captures complex relationships between sensor positions and modal identification quality, while maintaining geometrical constraints. This study illustrates the use of machine learning as an optimization tool in sensor placement and provides a concrete background for general applications in practical structural health monitoring studies.

Keywords: Sensor Placement Optimization, Optimal Sensor Placement (OSP), Machine Learning (ML), Neural Network, Bridge, Modal identification, Modal Assurance Criterion (MAC).

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1. INTRODUCTION

Structural health monitoring plays a fundamental role in the management and preservation of civil infrastructures, especially for historical structures such as masonry bridges [1,2]. Masonry arch bridges represent a structural typology of historical and engineering interest. These structures pose specific challenges in structural monitoring due to their complex geometries and nonlinear behaviors [3–5]. Their dynamic behavior, influenced by geometric configuration, boundary conditions, and conservation status, requires targeted and well-planned monitoring strategies [6,7]. The effectiveness of a monitoring system significantly depends on the placement of the sensors, an aspect that directly influences the quality and reliability of the acquired data [8,9]. Despite the importance of this phase, the optimal sensor configuration is frequently left to professional experience rather than systematic approaches [10,11].

Traditional methodologies for OSP mainly depend on deterministic strategies or optimization algorithms that often find challenging to deal with the multi-objective complexity of the problem [12–14].

Recently, Machine Learning (ML) techniques have demonstrated significant potential in addressing complex problems in the field of structural engineering [15,16]. In particular, Neural Networks (NN) offer the ability to learn complex relationships between different structural parameters and optimize multiple objectives simultaneously [17–19].

This article proposes an innovative methodology for optimizing the placement of sensors in masonry arch bridges, based on a feed-forward neural network. The developed approach integrates geometric considerations, dynamic behavior, and specific structural constraints, providing a mathematically rigorous and practically applicable tool to support decision-making in structural monitoring.

The work is divided into four main sections in addition to this introduction. Section 2 presents the mathematical formulation of the optimization problem, detailing the integration of the structural constraints specific to arch bridges. Section 3 describes the structure of the implemented NN. Section 4 presents the numerical validation of the method through tests on synthetic datasets. Finally, section 5 summarizes the main results obtained and outlines potential future developments.

2. POSITIONING OPTIMIZAZION

The positioning of sensors for monitoring masonry arch bridges has been optimized through a supervised learning method based on neural networks. This section outlines the problem formulation, and the approach used in its resolution.

The problem of optimal sensor placement in masonry arch bridges can be defined as an optimization problem aimed at finding locations that maximize the efficiency of the monitoring system. The problem can be formally articulated as a constrained optimization expressed by:

$$\min f(x) \quad \text{s.t.} \quad g(x) \leq 0 \tag{1}$$

where x is the vector of the decision variables, $f(x)$ is the objective function to be minimized, and $g(x)$ represents the constraints of the problem [20].

In the context of masonry arch bridges, the decision variables denote the presence or absence of sensors at each possible location on the structure. The objective function measures the efficiency of the configuration regarding the monitoring capacity, which is essential for historical structures as highlighted by Ramos et al. (2010) [21]. Constraints guarantee that the solution complies with certain structural requirements, which are necessary to assess the overall operation.

The ADAM (Adaptive Moment Estimation) algorithm was used to address this optimization problem, as it is a stochastic optimization method quite effective for non-convex optimization issues [22]. ADAM marks an advancement above conventional gradient-based algorithms, combining the benefits of AdaGrad and RMSProp into a single approach that has exhibited better efficiency across several applications.

The choice of ADAM for the current problem is driven by its adaptability for dealing with problems with gradients of different magnitudes and its resilience to noise, attributes particularly relevant to sensor site optimization. Salehi and Burgueño (2018) [23] note that such characteristics are helpful when the interactions among variables are complex and not easily predictable, which is common in structural monitoring applications. Furthermore, ADAM computational efficiency makes it particularly useful for large-scale problems where second-order optimization methods may be impractical [24].

The key equations that govern the parameters updating in the ADAM algorithm are the following:

$$m_t = \beta_1 \cdot m_{t-1} + (1-\beta_1) \cdot \nabla f_t(\theta) \tag{2}$$

Equation (2) estimates the first moment (moving average) of the gradient (m_t), where f_t is the objective function. The parameter β_1 is a decay parameter which governs the retention of past history: elevated values assign greater significance to prior gradients, resulting in more stable updates, albeit perhaps at a slower pace.

$$v_t = \beta_2 \cdot v_{t-1} + (1-\beta_2) \cdot [\nabla f_t(\theta)]^2 \tag{3}$$

Equation (3) estimates the second moment (variance) of the gradient (v_t), it measures the "dispersion" of recent gradients. As for β_1, also β_2 is a decay parameter, and determines how much weight is given to the most recent values of the gradient compared to historical values.

$$\widehat{m}_t = \frac{m_t}{1-\beta_1^t} \;\; ; \;\; \hat{v}_t = \frac{v_t}{1-\beta_2^t} \tag{4}$$

In Equation (4), $\widehat{m}_t$ and $\hat{v}_t$ are the corrected moment estimates after that a bias correction is applied to previous estimations.

$$\theta_{t+1} = \theta_t - \alpha \cdot \frac{\widehat{m}_t}{\sqrt{\hat{v}_t} + \varepsilon} \tag{5}$$

Finally, Equation (6) gives the updating rule for the model parameters θ. The learning rate α is adjusted for each parameter by dividing it by the square root of the corrected estimate of the second moment, together with a term ε that avoids division by zero. The adaptive normalization of the learning rate is key of the ADAM algorithm: parameters showing large but consistent gradients receive less updates, while parameters showing small but consistent gradients receive more updates.

In the context of sensor placement, the ADAM algorithm was executed with parameters consistent with recent literature [25,26]: β_1 = 0.9, β_1 = 0.999, α = 0.001, and ε = 10^{-8}.

A key aspect in the optimization of sensor placement for masonry arch bridges is the need to meet specific structural constraints. Certain elements of the construction, like the arch keys and the haunches of the central arch, should be necessarily monitored, as emphasized by Borlenghi, Saisi and Gentile (2024) [27]. Furthermore, the optimal configuration must include enough sensors to allow for a proper monitoring of the structure, a point highlighted by Papadimitriou (2004) [11] in his methodological examination of the parametric identification of structural systems. Thus, structural constraints have been integrated into the optimization problem as per the methodology suggested by Stubbs and Park (1996) [28], directing the ADAM algorithm towards solutions that fulfill these critical criteria for efficient structural monitoring.

3. NEURAL NETWORK ARCHITECTURE

This section describes the architecture of the neural network implemented to solve the optimization problem formulated previously. The approach is based on a feed-forward network designed to learn the relationships between structural parameters and optimal sensor configurations.

The adopted architecture is a multilayer feed-forward neural network, characterized by a progressive reduction in layer sizes up to the output layer. The structure proves particularly suitable for the problem at hand, as it allows for the processing of a significant number of input parameters and captures non-linear relationships between the bridge characteristics and the optimal sensor positions.

The network consists of an input layer, followed by three hidden layers with ReLU (Rectified Linear Unit) activation functions, and an output layer with a sigmoid activation function [29]. The choice of the sigmoid function in the last layer is motivated by the need to obtain values within the range [0,1], interpretable as the probability of sensor placement.

The input layer is designed to process two main categories of data:

- *Geometric parameters*: they include the total length of the bridge, the width of the deck, the thickness of the slab, the dimensions of the arches (spans and heights of the central and the side arches), the diameter of the arches, the number of piers, and their heights.
- *Modal parameters*: they include the first four natural frequencies, the associated modal shapes, and the values of the MAC (Modal Assurance Criterion) matrix.

The overall size of the input layer is determined by the sum of the dimensions of these parameters, resulting in a vector of 141 features (9 geometric parameters, 4 frequencies, 112 values for modal shapes (4 frequencies per 28 positions), and 16 elements of the MAC matrix).

The implemented architecture includes three hidden layers with decreasing dimensions, resulting in a first hidden layer of 256 neurons, a second hidden layer made by 128 neurons and finally a third hidden layer constituted of 64 neurons. Each hidden layer is followed by a ReLU activation function, defined as:

$$f(x) = \max(0, x) \tag{6}$$

This function introduces non-linearity into the network, allowing it to model complex relationships between input and output, while maintaining a stable gradient for positive input values.

To improve the model generalization and prevent overfitting, a batch normalization after each hidden layer and a dropout in the first two hidden layers have been implemented [30,31].

The output layer consists of 28 neurons, corresponding to the possible positions of the sensors on the structure. The sigmoid activation function is equal to:

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{7}$$

and transform the output into values between 0 and 1, interpretable as the probability of placing a sensor in each position.

For the training of the network, the ADAM (Adaptive Moment Estimation) optimization algorithm was used, characterized by a combination of momentum and learning rate adaptation [22]. The choice is motivated by ADAM ability to dynamically adapt to problems using first and second moment estimates of the gradient.

The implemented loss function reflects the formulation of the optimization problem presented in the previous section. The loss consists of a main term that quantifies the effectiveness of the proposed configuration and penalty terms that ensure compliance with structural constraints:

$$L(\theta) = MSE\left(y_{pred}, y_{target}\right) + \cdot \lambda_1 L_{constraints} \tag{8}$$

where MSE represents the mean squared error between the predicted configuration and the target configuration, $L_{constraints}$ quantifies the violation of structural constraints, λ_1 is the penalty coefficient, and θ represents the network parameters. This formulation of the loss function guides the learning process towards solutions that effectively balance the optimality of the configuration with the adherence to the structural constraints specific to masonry arch bridges.

The next section will present the numerical validation of this architecture, analyzing the model performance on a synthetic dataset representative of various arch bridge configurations.

4. NUMERICAL VALIDATION

The numerical validation of the proposed approach was conducted through a series of systematic tests on a synthetic dataset generated considering representative configurations of three-span masonry arch bridges. The validation dataset was generated considering parametric variations that reflect the typical characteristics of masonry arch bridges. The geometric parameters ranges are reported in Table 1.

Parameter	Dimension
Total length of the bridge	40 ÷ 60 [m]
Deck width	6 ÷ 8 [m]
Deck thickness	0.3 ÷ 0.5 [m]
Central arch span	8 ÷ 25 [m]
Side arch span	80% of the central arch span
Central arch rise	2 ÷ 6 [m]
Lateral arch rise	80% of the central arch rise
Thickness of arches	0.8 ÷ 1.2 [m]
Pile heights	5 ÷ 8 [m]

Table 1: Geometric parameters range.

For each geometric configuration, the modal characteristics were determined by solving an eigenvalue problem based on a simplified mass-stiffness model. The mass matrix was assumed to be diagonal, while the stiffness matrix was constructed considering the coupling between adjacent points of the structure. The first four natural frequencies and the corresponding mode shapes have been extracted.

Initially, a synthetic dataset representative of various arch bridge configurations was generated, each characterized by specific geometric parameters and modal properties. This dataset was processed to extract the relevant features and define the learning targets, incorporating the structural constraints related to the mandatory sensor positions. The training of the neural network was carried out using the ADAM algorithm, maintaining the optimization parameters described in the previous section. During the learning process, the network progressively refined its ability to propose optimal configurations, achieving satisfactory convergence after about 100 epochs (as shown by Figure 1).

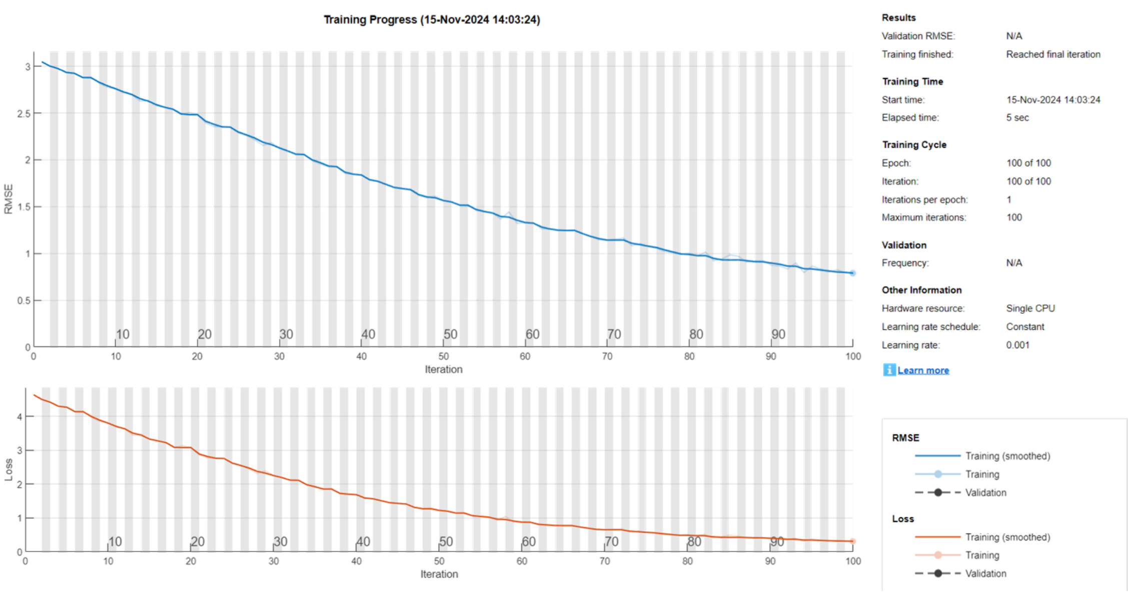

Figure 1: Training Process.

The validation results indicated good performance of the proposed model. The neural network demonstrated a remarkable ability to generalize, as evidenced by an average positioning accuracy of 92.3% evaluated on an independent test set. The mean squared error of 0.084 and the correlation coefficient of 0.91 further confirm the quality of the model predictions.

The constrained positions were correctly identified in all the analyzed cases, demonstrating the network ability to effectively incorporate these fundamental requirements. Similarly, the requirement for the minimum number of sensors has always been met in the proposed configurations.

Figure 2 shows an example of a proposed configuration for a three-arch bridge, highlighting the points with a placement probability greater than 0.8. It is observed how the configuration respects the mandatory positioning constraints and effectively distributes the remaining sensors to maximize modal coverage.

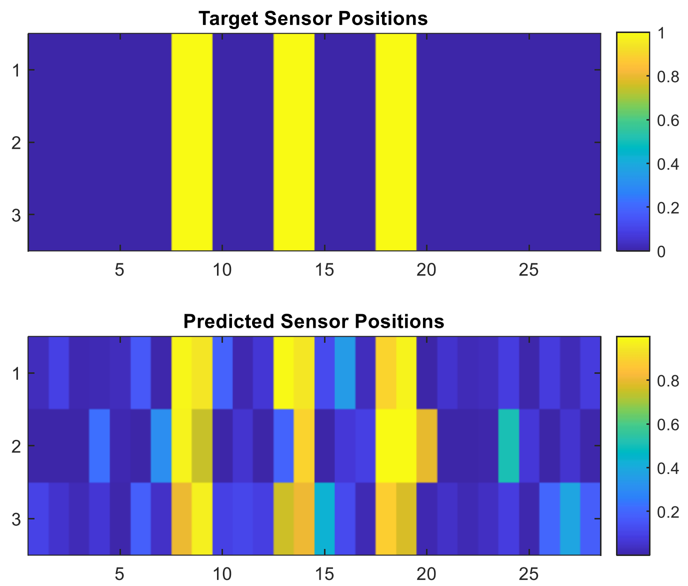

Figure 2: The proposed OSP for a three-arch bridge.

5. CONCLUSIONS

The present work has proposed an innovative methodology for optimizing the placement of sensors in masonry arch bridges, based on the implementation of a feed-forward neural network. The developed approach integrates geometric considerations, dynamic behavior, and specific structural constraints, providing a computationally efficient tool to support decision-making in structural monitoring. The mathematical formulation of the optimization problem has allowed for the definition of a coherent framework that balances several complementary objectives: the maximization of modal coverage, the optimization of measurement independence, and the efficiency of the configuration. The implementation of these objectives through a neural network has demonstrated the approach ability to learn complex relationships between structural parameters and optimal sensor configurations. The numerical validation conducted on a synthetic dataset has shown promising performance, with an average positioning accuracy exceeding 90% and full compliance with structural constraints. Particularly significant was the ability of the model to adapt to different geometric configurations, suggesting its potential applicability to a variety of masonry arch bridges.

Despite the encouraging results, the research presents some limitations that suggest directions for future developments. The synthetic dataset used for validation, although representative of different geometric configurations, cannot fully capture the complexity and variability of real structures. Validation on real cases, therefore, represents a natural development of the research, which would allow testing the effectiveness of the method in concrete operational conditions.

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