On the Joint Optimization of Energy Harvesting and Sensing of Piezoelectric Energy Harvesters: Case Study of a Cable-Stayed Bridge

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Abstract—Piezoelectric Energy Harvesters (PEHs) are typically employed to provide additional source of energy for a sensing system. However, studies show that a PEH can be also used as a sensor to acquire information about the source of vibration by analysing the produced voltage signal. This opens a possibility to create Simultaneous Energy Harvesting and Sensing (SEHS) system, where a single piece of hardware, a PEH, acts as both, a harvester and as a sensor. This raises a question if it is possible to design a bi-functional PEH device with optimal harvesting and sensing performance. In this work, we propose a bi-objective PEH design optimisation framework and show that there is a trade-off between energy harvesting efficiency and sensing accuracy within a PEH design space. The proposed framework is based on an extensive vibration (strain and acceleration) dataset collected from a real-world operational cable-stayed bridge in New South Wales, Australia. The bridge acceleration data is used as an input for a PEH numerical model to simulate a voltage signal and estimate the amount of produced energy. The numerical PEH model is based on the Kirchhoff-Love plate and isogeometric analysis. For sensing, convolutional neural network AlexNet is trained to identify traffic speed labels from voltage CWT (Continuous Wavelet Transform) images. In order to improve computational efficiency of the approach, a kriging metamodel is built and genetic algorithm is used as an optimisation method. The results are presented in the form of Pareto fronts in three design spaces.

Index Terms—Piezoelectric energy harvester, simultaneous energy harvesting and sensing, cable-stayed bridge, multi-objective optimization, Kriging surrogate model.

I. INTRODUCTION

ADVANCED wireless technologies and microelectronics have revolutionised the development of wearable devices, while the concept of the Internet of Things (IoT) has led to the deployment of smart equipment in remote areas where battery charging is challenging [1], [2], [3], [4]. To address the need for self-powered systems in such environments, energy harvesting techniques have become essential. One prominent avenue of research is kinetic energy harvesting, with Piezoelectric Energy Harvesters (PEHs) emerging as a popular choice. PEHs, based on piezoelectric materials like lead zirconate titanate (PZT), poly(vinylidene fluoride) (PVDF), aluminium nitride (AlN), and zinc oxide (ZnO), offer a promising approach to convert mechanical vibrations into usable electrical energy. The performance of a PEH significantly depends on its design, and by appropriately selecting its geometry and material the output voltage can be maximised [5]. Research in the literature aims to enhance the energy harvesting capabilities of wearable devices and remote IoT systems, ensuring their sustainability and functionality in challenging environments.

PEHs are primarily designed to convert vibrations from various sources into electrical power. However, there is a growing interest in utilising these devices as sensors to detect different environmental contexts. For instance, researchers have made significant progress in harnessing biomechanical energy from human motion using piezoelectric materials. By wearing a body-mounted piezoelectric device, not only can electricity be generated from human activities, but the resulting electrical signal can also serve as a distinctive signature for characterising specific activities such as running, walking, or jumping [6], [7], [8]. Additionally, the development of stretchable piezoelectric energy harvesters has paved the way for generating voltage from the motion of internal organs [9]. In vivo studies have demonstrated that voltage signals from cardiac devices can be utilised to detect important physiological parameters such as heart rate, endocardial pressure, and arterial blood pressure [10].

PEHs have demonstrated versatility as sensors, extending beyond applications related to human motion. They have found success in diverse areas, such as measuring water velocities in high-temperature and high-pressure pipes [11]. Additionally, energy harvesters installed on a vehicle have been used to measure ambient wind velocity and detect gas/liquid flow [12]. In the field of traffic monitoring, piezoelectric sensors attached on the pavement enable speed monitoring of passing vehicles as well as identifying the tire contact force [13]. Furthermore, significant advancements have been made in the development of cantilever-type MEMS, which now serve as acceleration sensors [14]. These examples demonstrate the diverse range of applications wherein piezoelectric materials have proven to be valuable as sensors.
Similarly, attaching a PEH device underneath a vibrating bridge offers more than just electricity generation from the bridge vibrations. The resulting voltage responses can be used for sensing. For instance, they can be utilised to detect the entry and exit times of vehicles on the bridge, providing valuable traffic information [15]. Moreover, these voltage responses can be employed to identify train passages, enabling efficient monitoring of railway activity [16]. Additionally, the use of PEHs as sensors allows for the detection of bridge damage, contributing to structural health monitoring [17].

Therefore, piezoelectric energy harvesters (PEHs) have great potential to provide both energy and contextual information, eliminating the need for dedicated sensors like accelerometers or strain gauges. This promising concept is known as Simultaneous Energy Harvesting and Sensing (SEHS) system [18]. Integrating these functions not only simplifies system design but also optimises energy usage by efficiently directing generated energy to power other system components, such as a transceiver used for cloud-based data transmission. The utilisation of SEHS systems based on piezoelectricity has already been studied in applications such as human activity recognition, demonstrating superior energy harvesting and sensing capabilities compared to using two separate PEHs, each dedicated to a specific task [7]. However, this technology still faces several challenges that need to be overcome for sustainable operations for IoT systems [19]. Designing a SEHS system requires a careful balance between efficient energy harvesting and high sensing accuracy. Although significant progress has been made in designing efficient PEHs for energy harvesting purposes [20], [21], [22], little is known about the impact of PEH design parameters, such as its geometrical shape, on its sensing performance.

In this work, we explore various PEH design spaces to understand the impact of design configurations on both energy harvesting as well as sensing accuracy. In the first study, we consider six different shapes of a cantilever-type PEH fed by an extensive vibration dataset collected from a large-scale operating cable-stayed bridge. The parametric study reveals that both energy harvesting efficiency and sensing accuracy depend significantly on the shape of the PEH, and there exists a trade-off between the harvesting and sensing performances. In the next step, we propose a joint optimisation framework and show that optimal design configurations form a Pareto front, which can be used by a designer to compromise between two objectives in each specific application.

The contributions of this paper can be summarised as follows:

1) Using real field datasets from an operating cable-stayed bridge, we make the first attempt in exploring the impact of PEH geometry on both energy harvesting and sensing accuracy in the context of a vehicle speed estimation.

2) We present a deep learning framework to evaluate the vehicle speed sensing performance of PEHs with various designs.

3) We report evidence, for the first time, that there are design trade-offs between energy harvesting and sensing, i.e., PEH designs that provide peak energy do not provide peak sensing accuracy.

4) We propose a design optimisation framework to efficiently tackle the selection of PEH geometries that address the trade-off between their energy harvesting and sensing performances. This multi-objective formulation ultimately leads to a manifold of geometries (Pareto front).

The following paragraphs provide a concise overview of the organisation and content of the remaining sections in this paper.

Section II delves into the details of the cable-stayed bridge, which serves as the basis for the case study in this research. It comprehensively describes the bridge, including its instrumentation.

In Section III, the theoretical framework of the piezoelectric energy harvesting (PEH) model is introduced. This framework enables the estimation of the voltage signal generated by any PEH device installed on the bridge. To achieve this, the model incorporates experimental measurements of the traffic-induced acceleration of the bridge as input.

Section IV presents the deep learning framework used to infer vehicle speed on the bridge. It provides a comprehensive description of the framework, including its key components and methodology. Additionally, a comparative analysis of neural network architectures is conducted to select the most suitable one for our application.

Moving on to Section V, the performance of the deep learning framework is analysed on the cable-stayed bridge presented in Section III. We initially assess its performance using the direct acceleration signal as input, establishing a benchmark for subsequent analyses. Subsequently, the framework is studied using images derived from the voltage signal as input to the CNN, considering six different geometries to examine their impact on accuracy.

In Section VI, various piezoelectric harvester geometries are evaluated to investigate the potential trade-off between sensitivity and energy harvesting. We assess the sensing accuracy and average daily energy generation achieved by these devices, aiming to understand the relationship between these two factors, sensing and harvesting performance.

Finally, Section VII presents and implements a bi-objective optimisation framework through an illustrative case study on the same bridge discussed in previous sections. The framework is explained in detail, and an example is tested. The paper concludes with Section VIII.

II. Case Study: A Cable-Stayed Bridge

The study will be conducted on a cable-stayed bridge situated over the Great Western Highway in the state of New South Wales (NSW), Australia (Fig. 1). The bridge comprises a single traffic lane and one pedestrian lane, with a maximum load capacity of 30 tons. Although vehicles can travel in both directions, this study focuses only on the south-north traffic flow. The bridge’s deck is supported by four longitudinal girders, internally connected by seven cross girders (CGs), as depicted in Fig. 2.

Underneath the bridge deck, an array of sensors has been installed, including accelerometers and strain gauges. The
accelerometers used are model number 2210-002, manufactured by Silicon Design, Inc. These accelerometers incorporate a 1210L micro-machined capacitive accelerometer, capable of detecting accelerations within the range of \( \pm 2 \text{ g} \). They have an output noise of \( 10 \mu g/\sqrt{\text{Hz}} \) and a sensitivity of 2,000 mV/g. The strain gauges employed are shear rosettes, mounted at various longitudinal locations along the bridge.

For the purposes of this study, we have adopted one accelerometer sensor (A1) and two pairs of strain gauge sensors (SS1:SS4), as shown in Fig. 2. The signal conditioning and data logging system consists of an embedded PC and HBM Quantum-X data logger, which records the data. This system provides an integrated and reliable device for logging high-quality data with 24-bit resolution and a bandwidth capability of 0 to 3 kHz. The hardware combines instrument excitation, voltage regulation, digitisation, anti-aliasing filters, and data logging. The logging software used is Catman, which collects data from all channels at a default sample rate of 600 Hz with an anti-aliasing filter. The filter is a fourth-order Bessel low-pass filter with a 3 dB cut-off frequency of 100 Hz.

The data collected from accelerometer A1 will be utilised to estimate the potential harvested energy from passing traffic and infer the corresponding traffic speed. Additionally, the two pairs of strain gauge sensors will be used to estimate the ground-truth velocity, which will then be used to label samples in the training and testing database for the Neural Network (NN) model. The vehicle speed is independently estimated using strain gauge sensors SS1-SS2 and SS3-SS4.

By considering the known distances between the sensors under the bridge span, the time difference taken by a vehicle’s axle to travel from one sensor to another allows for the estimation of the vehicle’s speed (for more details, refer to [23]). Although only one pair of sensors can be used for speed estimation, this study utilises the average speed between the two pairs to improve the reliability of the results.

III. PEH IGA MODEL

Several models to estimate the dynamic response of a cantilever-type piezoelectric energy harvester exist in the literature. In this work, we use the model based on the Kirchhoff-Love plate theory and Hamilton’s principle for electro-mechanical bodies, solved numerically by the IsoGeometric Analysis (IGA). The model was proposed in [21] and was shown to be highly accurate at reasonable computational cost. A schematic of a PEH is shown in Fig. 3. The device is assumed to have a rectangular shape with width \( W \) and length \( L \), consisting of a substructure layer of thickness \( h_s \) and two piezo-electric layers of thickness \( h_p \) (such configuration is called bimorph), mounted on a vibrating base. To simplify all the subsequent studies, only the impact of the parameters \( L \) and \( W \) on energy harvesting and detection accuracy will be analysed. This means that these parameters are considered design variables, while the material parameters and thicknesses \( h_s \) and \( h_p \) are assumed to be constant.

According to the IGA, B-Splines \( N_l \) are used to parameterise the device’s domain and approximate the relative deflection \( w \). We further use Modal Order Reduction approach, which consists of approximating \( w \) by a truncated expansion of the first \( K \) mode shape vectors \( w \approx w_o = \Phi_o \eta \). Here, \( \Phi_o \in \mathbb{R}^{N \times K} \) is the matrix which contains the \( K \) first mode shape vectors \( \phi_i \) and \( \eta \in \mathbb{R}^{K \times 1} \) denotes the modal coordinates. Therefore, the procedure leads to a coupled system of differential equations of the form

\[
\ddot{\eta} + c_o \dot{\eta} + k_o \eta - \theta_o \dot{v}(t) = f_o a_b(t) \\
C_p \ddot{v}(t) + \frac{\nu(t)}{R_l} + \Theta' \Phi_o \dot{\eta} = 0
\]

where the equation (1) corresponds to the reduced mechanical equation of motion with electrical coupling, while the equation (2) corresponds to the reduced electrical circuit equation with mechanical coupling. Here, \( k_o \in \mathbb{R}^{K \times K} \) is the reduced stiffness matrix, \( c_o \in \mathbb{R}^{K \times K} \) is the reduced mechanical damping matrix, \( f_o \in \mathbb{R}^{K \times 1} \) is the mechanical forces vector, \( \Theta \in \mathbb{R}^{N \times 1} \) is the reduced electro-mechanical coupling vector, \( \theta_o \in \mathbb{R}^{K \times 1} \) is the electro-mechanical coupling vector; \( C_p \) is the capacitance and \( R_l \) is the external electric resistance;
a_b(t) is the base acceleration and v(t) is the output voltage; dots denote derivatives with respect to time t. This model was studied in detail in [25].

In a particular case when the base acceleration is a harmonic signal, i.e. \( a_b(t) = A_b e^{i \omega t} \), one can show that the output voltage is also harmonic, i.e. \( v(t) = V_\nu(\omega) e^{i \omega t} \) (where \( i = \sqrt{-1} \)), and the Frequency Response Function (FRF), \( H = H(\omega) \), can be defined to relate the amplitudes of the output voltage \( V_\nu(\omega) \) and the excitation acceleration \( A_b \) for a specific frequency \( \omega \) from the equations (1) and (2):

\[
H = H(\omega) = \frac{V_\nu(\omega)}{A_b} = i \omega \left( \frac{1}{R_l} + i \omega C_p \right)^{-1} \Theta^T \Phi_o \times \left( -\omega^2 I_o + j \omega \Theta_o + k_o + i \omega \left( \frac{1}{R_l} + i \omega C_p \right)^{-1} \Theta_o \Theta^T \Phi_o \right)^{-1} f_o
\]

(3)

From the differential equations (1) and (2), it is also possible to estimate the voltage signal in time when the piezoelectric device is subjected to an arbitrary base acceleration \( a_b(t) \), which in this study represents the acceleration measured from a vibrating bridge as a result of passing traffic. The system of differential equations can be written in its state-space form as

\[
\dot{\mathbf{Z}} = \mathbf{A} \cdot \mathbf{Z} + \mathbf{b} \cdot a_b(t)
\]

(4)

where

\[
\mathbf{Z} = \begin{bmatrix} \eta \\ \dot{\eta} \\ v \\ \dot{v} \end{bmatrix}, \quad \mathbf{A} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ -k_o & -c_o & 0 & 0 \\ 0 & -\theta_o \Phi_o & -\frac{1}{c_p} \Theta_o^T \Phi_o & -\frac{1}{c_p} \Theta_o^T \Phi_o \\ 0 & 0 & 0 & 0 \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} 0 \\ 0 \\ f_o \\ 0 \end{bmatrix}
\]

Simulink ode45 solver is used to solve this system for \( v(t) \). In what follows, we will investigate how the solution of system (4) depends on the geometric parameters: length \( L \) and width \( W \). To emphasise that the output voltage \( v(t) \) is obtained for a specific geometry \( x \), where \( x = \{L, W\} \), we use notation \( v(t) = v(t, x) \). The corresponding electrical energy, \( E(x) \), generated in time interval \( t \in [t_1, t_2] \), can be calculated from the following equation:

\[
E(x) = \int_{t_1}^{t_2} \frac{v^2(t, x)}{R_l} dt
\]

(5)

Therefore, based on the framework detailed in this section, one can obtain the voltage generated by a PEH in response to the passage of a vehicle over the bridge, characterised by the base acceleration \( a_b(t) \). In the next section, a procedure to obtain the speed of a moving vehicle from the acquired voltage signal \( v(t) \) is presented.

IV. DEEP LEARNING APPROACH

In this section, a deep-learning-based framework is presented to infer a passing vehicle’s speed from the voltage signal generated by a PEH installed under the bridge. In a previous work, Zhou et al. [26] presented a methodology to infer vehicle speed using the acceleration signal response of bridges purely. In the present work, this methodology is adapted and validated, incorporating the generated voltage signal from a PEH as the primary information source to infer the vehicle’s speed.

As indicated in Fig. 4, two main parts can be identified in this framework: sample generation and Convolutional Neural Network (CNN) training and testing. Sample generation procedure consists of the following four steps:

1. From the continuous bridge response database, the time window corresponding to a passing vehicle, which we call an event, is extracted. An event is defined based on the threshold criteria, i.e. the acceleration magnitude exceeding 0.015 m/s² indicates the presence of an event. As the primary objective of this study is to investigate the relationship between device design and sensing performance, we have chosen to simplify the sensing task by not considering cases with multiple vehicles on the bridge. Each event is taken to be 25 second. This selection is based on the span length of the bridge under investigation, and the min-max speed range on this bridge. An event is extracted in such a way, that the peak is always located at 10 seconds, i.e. the peak is identified first, then the time window starting 10 second before the peak and ending 15 second after the peak is considered. For each event, we extract the acceleration and strain signals.

2. The acceleration signal of an event is then used as a base acceleration input \( a_b(t) \) in the PEH IGA model, described in Section III and the corresponding voltage signal \( v(t) \) is obtained.

3. For each event, the vehicle speed label is assigned from the strain measurements following the procedure explained in [23].

4. The raw time signal of the voltage \( v(t) \) is post-processed using the time-frequency analysis. Continuous Wavelet Transformation (CWT) with Morlet Wavelet is employed, following the recommendation in [26], and the corresponding CWT image is generated.

The chosen CNN architecture for this work is AlexNet. It was selected based on its successful implementation in vehicle classification, as presented by Zhou et al. [26]. Additionally, a comparative analysis involving various CNN architectures was conducted, as outlined in Appendix A. This
comparative study aims to evaluate the performance of different CNN models and ultimately demonstrate the suitability of AlexNet for the given task. Figure 5 provides an illustration of AlexNet’s architecture, which consists of a total of eight layers. The initial five layers are convolutional layers, some of which are followed by max-pooling layers, while the final three layers are fully connected (FC) layers.

The second part of the methodology focuses on training and testing the CNN. This phase consists of the following steps:

1. Constructing the CWT images database by following the sample generation procedure. The dataset is divided into two sets: one set for training and another set for testing purposes. The selected CNN architecture, AlexNet, undergoes initial pre-training using the ImageNet database [28]. ImageNet is widely recognised for its utilisation in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) [29]. It comprises over a million images categorised into 1000 object classes. This pre-training step is crucial as it allows AlexNet to leverage a large number of training images. Consequently, this approach enables the network to effectively extract fundamental features from the input images while utilising a reduced number of CWT images. This pre-training establishes a strong foundation in the lower-level layers of the network.

2. By employing a transfer learning methodology, the last layers of the pre-trained CNN are fine-tuned using the CWT image database. This involves replacing the original last layer with a new layer that incorporates higher learning rates. Subsequently, the network is trained specifically for the task of speed identification using CWT image data. This approach leverages the knowledge and features learned from the pre-trained CNN while optimising its performance to accurately predict speed based on the CWT image information. By employing a combination of transfer learning and targeted dataset training, the model’s capabilities can be significantly enhanced in terms of speed identification, even when using a reduced database.

4. Finally, the accuracy of the trained neural network is assessed by conducting cross-validation using the test data. This validation process allows us to evaluate the model’s performance on unseen data and verify its accuracy in predicting speed. By employing cross-validation, a robust assessment of the neural network’s capabilities is ensured which validates its effectiveness.

V. SENSING ACCURACY

In this section, the methodology proposed in section IV is implemented and analysed. In order to use a PEH as a sensor, we expect its sensing accuracy (i.e. the accuracy of traffic speed labelling based on voltage signal $v(t)$) to be comparable with the accuracy of acceleration-based sensing (i.e. the accuracy of traffic speed labelling based on bridge acceleration signal $a_b(t)$). Hence, we first conduct a preliminary study (A), where the proposed sensing framework is applied to bridge acceleration events directly, and its accuracy is assessed. In the next study (B), we consider six configurations of PEHs, corresponding to six various values of length $L$, while all other parameters are kept constant, and label the speed of passing traffic based on the voltage signals produced by the PEHs.

For each event, time-frequency analysis using CWT is performed to obtain two-dimensional time-frequency images, either for acceleration signal in case (A) or for voltage signal in case (B). For the sake of consistency, all images are produced considering a time limit of [5, 25] seconds and a frequency limit of [0, 200] Hz.

In each implementation, the database is divided randomly into two sets for training and testing processes, containing 70% and 30% of the data, respectively. Also, the training-testing process is performed multiple times to reduce the stochastic factors. A total of 1265 samples are considered, which are classified into three different labels, as presented in Fig. 6.

A. Benchmark Case: Acceleration-Based Sensing

In this section, we present results for the acceleration-based sensing, which will serve as a benchmark for the voltage-based sensing. The results obtained from this study are compared with counterpart results reported in the literature performed on an experimental setup in a laboratory [26].

An example of an event and the corresponding CWT image are shown in Fig. 7a and 7b, respectively.

The training process is carried out five times, to reduce the impact of random factors, where, each time, 70% of the data is
randomly extracted for training. In Fig. 8a and 8b, the accuracy and loss curves for five training processes are, respectively, presented. From these figures, it can be seen, that the loss continuously decreases across the epochs, and the accuracy tends to converge to 100% at about 50 epochs. Furthermore, Fig. 8c presents the accuracy obtained from the testing dataset. The average accuracy of the five testing sets is 92.1%, which is quite good compared to 92.9% - 98.8%, reported in [26] using experimental data in contrast to field data used in the present work. Additionally, the confusion matrix of the testing set 5 is presented in Fig. 8d.

B. Study Case: Voltage-Based Sensing

In this section, the full framework proposed in section IV is employed for six different PEH designs. The materials of the devices are PZT5A and bronze [21]. Although materials affect the dynamic behaviour of devices and could affect detection performance, the focus of this research is to study the impact of device shape. The devices share the same geometric parameters, except for the length $L$, which is taken as 5, 10, 15, 20, 25, and 30 cm. Meanwhile, the width $W$, piezoelectric thickness $h_p$ and substructure thickness $h_s$ are 5 cm, 0.25 mm and 0.50 mm, respectively. Other important considerations for the PEH model is that the external electrical resistance is taken as $R = 100\,\Omega$, and the damping coefficients are assumed to be $\alpha = 14.65\,\text{rad/s}$ and $\beta = 10^{-5}\,\text{rad/s}$ [21].

Fig. 9 presents the FRFs of the six studied devices, where the effect of varying the length $L$ on the dynamic response can be seen, i.e. the resonant frequencies vary as function of the length $L$. Moreover, as $L$ increases, the device tends to be more flexible with more modes appearing in the range of 0 - 200 Hz. In fact, the selection of the six PEHs for this study is based on the significant differences in their FRFs, which, as will be discussed later, result in variations in the CWT images that are directly related to sensing accuracy.

To evaluate our model effectively, given the size and imbalance of our database, we have opted for a random sub-sampling cross-validation approach with stratified sampling. This approach consists of fifty iterative training and validating processes on different random but stratified subsets of the data. By employing stratified sampling, we ensure that each subset used for training and validation maintains a proportional representation of the different classes, thus accounting for the database’s inherent imbalance. This methodology aims to estimate the average accuracy of the model with greater reliability. Fig. 10 presents the mean value and error bars for the six devices considered in this study, and the benchmark accuracy, corresponding to the acceleration-based sensing, shown in the dotted black line. The PEH’s accuracy varies with $L$, reaching the highest value for the device with $L = 25$ cm, which is, interestingly, higher than the benchmark accuracy. We can see that the accuracy for $L = 20$ cm and $L = 30$ cm is also comparable with the benchmark case and for $L = 5, 10, 20$ cm, the accuracy of voltage-based sensing is lower than the accuracy of acceleration-based sensing. To interpret these results, it is necessary to consider that CNN extracts information from the time-frequency images. Fig. 11 presents the CWT images of the voltage signals generated from the reference acceleration window, previously presented in Fig. 7, by the six PEHs considered in this study. The pink dashed lines represent the resonance frequencies of each device identified from the FRFs, presented in Fig. 9. As shown in Fig. 11, the highest values of the wavelet coefficients, and consequently the most informative parts of these images, are centred close to some resonant frequencies of each PEH device, also influenced by the resonance frequencies of the bridge. Further, since
Fig. 9. Frequency Response Functions of the six devices with length of (a) 5 cm (b) 10 cm (c) 15 cm (d) 20 cm (f) 25 cm (g) 30 cm.

Fig. 10. Bar plot of accuracy from five different training processes for the six devices studied and the benchmark accuracy 92.1% based on acceleration signal (shown in black dotted line).

devices with different length are associated with different resonance frequencies, the information they provide will differ, which consequently leads to different sensing performances.

Next, a question arises on how the sensing accuracy and power generation are correlated. This issue will be addressed in the next section.

VI. SIMULTANEOUS ENERGY HARVESTING AND SENSING

In this section, the electrical energy harvested from each of the six PEH devices is studied to establish a correlation between the optimal design in terms of sensing and energy harvesting performances. Five 12-hour continuous time windows of acceleration response, between 8 am and 8 pm, are used to estimate the six candidates’ average energy generated from five separate days. The energy is estimated using equation (5).

Fig. 12a presents the harvested energy, and the corresponding variation. From this figure, it is evident that the highest energy generation corresponds to the device with a length of 15 cm. This is explained by analysing Fig. 12b, where the acceleration frequency spectrum of one 12-hour acceleration window from the bridge is compared with the FRFs of the six PEH devices. It can be seen that the resonance frequency of the optimal device with a length of 15 cm coincides well with dominant parts of the base excitation with frequencies around 21 Hz, which results in a higher energy generation compared to the other geometries.

Further, Fig. 13 shows the sensing performance of the six PEH devices together with the corresponding energy harvesting performance. From this figure, it is implied that there is no correlation between the optimal geometries in terms of sensing performance and energy harvesting performance, i.e., we cannot identify a device, which is optimal for both, energy harvesting and sensing. This observation opens up
a single PEH. In order to estimate the sensing accuracy, it is necessary to build the complete training and testing database to subsequently carry out the training process on multiple occasions to estimate the expected average accuracy. While in order to quantify the energy harvesting efficiency, it is necessary to perform the numerical integration over numerous long time windows to estimate a representative expected value. When the number of design variables increases, the space of possible geometries also increases, and the optimisation problem quickly becomes computationally unfeasible.

Surrogate modelling techniques are an attractive alternative to deal with this problem. A surrogate model (also known as a metamodel) consists of an efficient approximate relationship between the input and output of a system, using only a limited call to the original high fidelity model. Among surrogate techniques, the Kriging model [30] stands out over other approaches due to its ability to indicate the level of prediction confidence at the un-sampled point, and its good performance using a reduced number of sample points [31]. In this study, two Kriging models are implemented following the guidelines discussed in [21]. The input of each model corresponds to the design variables \( \mathbf{x} \) of a PEH device. We consider three design spaces, consisting of either \( L \) or \( \{L, W\} \), as will be defined later. The output corresponds to one of the objective functions: the amount of produced energy, denoted by \( E(\mathbf{x}) \) or sensing accuracy, denoted by \( S(\mathbf{x}) \). Since the Kriging metamodels provide highly accurate approximations of quantities \( E(\mathbf{x}) \) and \( S(\mathbf{x}) \), in what follows we will not distinguish if the energy/sensing accuracy is obtained from the Kriging metamodel or from the original high fidelity model, and use a single notation: \( E(\mathbf{x}) \) or \( S(\mathbf{x}) \).

VII. JOINT OPTIMISATION FRAMEWORK

The study presented in section VI reveals that energy harvesting efficiency and sensing accuracy significantly depend on the shape of the PEH. Based on the results already discussed, it is possible to state that the design of a bi-functional PEH is not a trivial task because no single configuration simultaneously maximises both. In this regard, a multi-objective optimisation framework is proposed to efficiently tackle the selection of PEH geometries that address the trade-off between its energy harvesting and sensing performances. This multi-objective formulation ultimately leads to a manifold of geometries (on the boundary of the feasible objective space) called the Pareto front. When no additional information is available from the context, all the Pareto front solutions are considered equally good, despite some being better in one objective but at the same time worse in the other objective, than the other Pareto front points. The proposed optimisation framework adopts a Genetic Algorithm (GA) employing surrogate metamodels to quantify the energy harvesting performance and sensing accuracy of different geometries. Details of this optimisation scheme are given next.

A. Kriging Surrogate Modeling

One of the main challenges of the present optimisation problem is the long computational times to estimate the sensing accuracy and the energy harvesting performance of a single PEH. In order to estimate the sensing accuracy, it is necessary to build the complete training and testing database to subsequently carry out the training process on multiple occasions to estimate the expected average accuracy. While in order to quantify the energy harvesting efficiency, it is necessary to perform the numerical integration over numerous long time windows to estimate a representative expected value. When the number of design variables increases, the space of possible geometries also increases, and the optimisation problem quickly becomes computationally unfeasible.

Surrogate modelling techniques are an attractive alternative to deal with this problem. A surrogate model (also known as a metamodel) consists of an efficient approximate relationship between the input and output of a system, using only a limited call to the original high fidelity model. Among surrogate techniques, the Kriging model [30] stands out over other approaches due to its ability to indicate the level of prediction confidence at the un-sampled point, and its good performance using a reduced number of sample points [31]. In this study, two Kriging models are implemented following the guidelines discussed in [21]. The input of each model corresponds to the design variables \( \mathbf{x} \) of a PEH device. We consider three design spaces, consisting of either \( L \) or \( \{L, W\} \), as will be defined later. The output corresponds to one of the objective functions: the amount of produced energy, denoted by \( E(\mathbf{x}) \) or sensing accuracy, denoted by \( S(\mathbf{x}) \). Since the Kriging metamodels provide highly accurate approximations of quantities \( E(\mathbf{x}) \) and \( S(\mathbf{x}) \), in what follows we will not distinguish if the energy/sensing accuracy is obtained from the Kriging metamodel or from the original high fidelity model, and use a single notation: \( E(\mathbf{x}) \) or \( S(\mathbf{x}) \).

B. Illustrative Implementation

Three optimisation cases are performed to evaluate the effectiveness of the proposed framework and understand the trade-off between the power generation and sensing accuracy of a PEH. These cases are based on three different design spaces for the parameters \( L, W \) for a bimorph PEH. The layers’ thicknesses are fixed (\( h_p = 0.25 \text{ mm} \) and \( h_s = 0.50 \text{ mm} \)). The materials of the devices are PZT5A and bronze (properties are given in Ref. [21]), the electrical resistance \( R_e = 100\Omega \) and the damping coefficients \( \alpha = 14.65 \text{ rad/s} \) and \( \beta = 10^{-5} \text{ rad/s} \). The three design spaces are given by:

- **Design Space 1.** \( \mathbf{x} = \{L\}: L \in [10, 55] \text{ cm}, W = 5 \text{ cm} \)
- **Design Space 2.** \( \mathbf{x} = \{L\}: L \in [10, 55] \text{ cm}, W = L \)
- **Design Space 3.** \( \mathbf{x} = \{L, W\}: L \in [10, 55] \text{ cm}, W \in [10, 55] \text{ cm} \)

Two kriging metamodels are trained for each design space to perform low computational cost output predictions for \( \{E(\mathbf{x}), S(\mathbf{x})\} \). In the case of Design Spaces 1 and 2, 50 support points are sampled uniformly. On the other hand, as the number of design variables in Design Space 3 is two, 1000 samples are considered, which are generated with a Latin hypercube sampling algorithm. On one hand, the harvested energy is calculated by averaging the values obtained from five separate 12-hour continuous time windows on the bridge. This estimation follows the methodology detailed in Section III. On the other hand, the sensing performance is determined...
by averaging the accuracy obtained from fifty training-testing iterations of the framework described in Section IV. For illustration, Fig. 14 shows the data of the support points and the surrogate approximation for $E(x)$ and $S(x)$ in Design Space 1. Here, the entire process of training the metamodel and generating the database takes approximately 30 hours using the Gadi High-Performance Computer (HPC) at the National Computational Infrastructure (NCI), which is equipped with NVIDIA V100 GPUs. This process is executed only once. Consequently, the metamodel is capable of producing outputs with errors below 0.81% for harvested energy and 0.52% for sensing accuracy, taking this in less than 1 second.

The optimisation problem is formalised as follows

$$\mathbf{x}^* = \arg \max_{\mathbf{x} \in \mathcal{X}} \{E(\mathbf{x}), S(\mathbf{x})\}$$ \hspace{1cm} (6)

The optimisation process was implemented in Matlab using the `gamultiobj` built-in function, which utilises the Non-dominated Sorting Genetic Algorithm II (NSGA-II). NSGA-II evolves a population of candidate solutions iteratively by creating offspring solutions from selected parent solutions. In this implementation, the initial population consisted of 100 individuals. The parent solutions were selected using Tournament Selection, where a subset of individuals is randomly chosen from the population, and their fitness values are compared to determine the winners. In this case, the tournament size was set to 4 individuals, and the crossover fraction was set to 0.8, representing the portion of the selected population without considering the elite individuals (the top solution to the problem).

In this context, the candidate solutions are encoded as chromosomes, which are structures representing the values of the decision variables that define these solutions. Genetic operators, namely crossover and mutation, are applied to the parent solutions to create offspring solutions. Subsequently, the population is updated using a non-dominated sorting algorithm and a crowding distance-based selection operator. The non-dominance rank assigns a rank to each solution based on its dominant relationship with other solutions, while the crowding distance measures the density of solutions around a specific solution.

This process of selection, reproduction, and evaluation is repeated until a termination condition is met. In this case, the termination condition is defined as reaching the maximum number of generations, set at 400 generations, and the average relative change in the fitness function value, which is defined as $10^{-4}$.

The optimisation results are presented in Fig. 15. Here, Fig. 15a shows $E(\mathbf{x})$ for Design Spaces 1 and 2, where the optimal geometries resulting from the optimisation process (Pareto front points) are also given. Fig. 15b shows $E(\mathbf{x})$ for (two-dimensional) Design Space 3, together with the optimal designs from the corresponding Pareto front. Functions $S(\mathbf{x})$ for Design Spaces 1 and 2 with their optimal geometries are presented in Fig. 15c and 15d, respectively. The function $S(\mathbf{x})$ for Design Space 3 is presented in Fig. 15e. Finally, Fig. 15f presents the Pareto front for the two objectives $E(\mathbf{x})$ and $S(\mathbf{x})$ for the three design spaces.

The competition between the objectives is evident in all three design spaces. The extremes of the Pareto front indicate the optimal designs for $E(\mathbf{x})$ and $S(\mathbf{x})$. In particular, it is possible to observe the gap between optimal values. In terms of sensing accuracy, its value varies within [91, 94.5]% across all optimal designs. In terms of energy harvesting performance, the amount of energy varies considerably between designs, with most energy produced in Design Space 3. This is an expected result, since the two design variables in Design Space 3 are independent, so this design space is larger and contains the other two design spaces.

The conventional approach to designing a Piezoelectric Energy Harvester (PEH) involves adjusting the device’s natural frequencies to match those of the vibration source. Therefore, as a reference design, we chose a device with dimensions of $44.6 \times 5$ cm, whose natural frequency is tuned with the first frequency of the bridge. This reference device achieves an output (sensing accuracy, harvested energy) of ($92.1\%$, $2.11 \times 10^{-5}$ J). The device optimal for energy production (far left point of the Pareto front in Design Space 3 in Figure 15f), achieves an output of ($91.6\%, 20.01 \times 10^{-5}$ J), which represents a remarkable increase of 16.5 times in terms of energy generation and a slight decrease of 0.5% in sensing accuracy in comparison with the reference design. Furthermore, the device optimal for sensing (far right point of the Pareto front in Design Space 3 in Figure 15f) achieves an output of ($94.5\%, 3.82 \times 10^{-5}$ J). This corresponds to a 2.4% increase in accuracy and a three times increase in energy in comparison with the reference solution.

In general, devices optimised for sensing accuracy tend to have a natural frequency around 8 Hz. Conversely, devices optimised for energy generation align their natural frequency with one of the resonant frequencies of the bridge, specifically at 2.7 Hz or 20 Hz. This has led to the concept of designing devices that incorporate sub-harmonic resonance frequencies to address these different objectives functionalities. However, while this approach aims to address the trade-off issue, it does not completely eliminate it. It is crucial to consider that tuning one of these sub-harmonics to a frequency different than the resonant frequency of the bridge will result in sub-optimal power generation for that particular device. This is because the sub-harmonic can potentially be adjusted to tune with a resonant frequency of the bridge, leading to improved power-harvesting performance. Some promising options that offer the potential for tuning into sub-harmonic
Fig. 15. (a) Energy Harvested for Design Spaces 1 and 2. (b) Energy Harvested for Design Space 3. (c) Sensing Accuracy for Design Space 1. (d) Sensing Accuracy for Design Space 2. (e) Sensing Accuracy for Design Space 3.

Fig. 16. (a) Energy per unit of area for Design Spaces 1 and 2. (b) Energy per unit of area for Design Space 3. (c) Pareto front with optimal geometries for the maximisation of $E(x)/A(x)$ and $S(x)$ in Design Spaces 1, 2 and 3.

devices resulting from the design space optimisation process in Design Space 3 have dimensions of $15.73 \times 51.32$ cm for energy generation and $29.17 \times 40.01$ cm for sensing, illustrating a notable difference in size. In order to make a fair comparison between the design spaces, another optimisation process is carried out considering the energy per unit area. The gap between both objective functions is comparable in the three designs. The best results are obtained in Design Space 3. This agrees with what was discussed earlier: Design Space 3 is larger and includes Design Space 2. This result shows that increasing the number of design variables could improve both objective functions’ performance; however, the trade-off between two objectives exists in all design spaces. Finally, the variation of the optimal geometries in the Pareto front is also notorious, going from large to small devices, hence the final design choice may ultimately depend on other design requirements.

VIII. CONCLUSION

Using real vibration datasets from a cable-stayed bridge, we studied the performance of six PEH geometries in terms of both energy harvesting and sensing to correctly label the
travelling speed of vehicles passing over the bridge. We found that there is no clear correlation between energy harvesting and sensing performance for a PEH. In other words, an optimum harvester may not necessarily act as an optimum sensor.

This finding motivated the development of a rigorous design framework for joint optimisation of dual-function PEH devices that are expected to provide both energy harvesting and sensing functionality. A comprehensive study case in a real-world application was carried out to show the potential of the framework to obtain a manifold of optimal geometries (Pareto front). By directing our attention to the extreme values of the Pareto front, where one objective function is given priority, the optimisation processes yielded notable improvements. These enhancements led to a remarkable increase of over 16.5 times in energy and an improvement of 2.4% in sensing accuracy. Ultimately, the designer is the one who decides which geometry to select based on the design requirements.

Although the optimisation framework is a good tool for understanding the trade-off between the multi-functionalities of a PEH, more studies are needed to improve the sensing performance using PEH, e.g., novel NN models. This work is the first effort to study the impact of a PEH shape on simultaneous energy harvesting and sensing and encourages future works in this direction.

APPENDIX A

We present the results of voltage-based sensing from a piezoelectric energy harvester (PEH) using various CNN architectures, namely AlexNet [34], GoogleNet [35], ResNet18 [36], ResNet101 [36], VGG16 [37], and VGG19 [37]. The complete framework described in Section IV is employed for the PEH design. For this study, we have chosen a bimorph configuration for the PEH device, utilising PZT5A and bronze materials [21]. The piezoelectric layers have dimensions of $150 \times 0.25$ mm, while the substructure measures are $150 \times 0.50$ mm. The natural frequency of the device is adjusted to align with the frequencies exhibiting high amplitudes of vibration on the bridge. Additionally, it is important to note that the external electrical resistance is set to $R = 100 \Omega$, and the damping coefficients are assumed to be $\alpha = 14.65$ rad/s and $\beta = 10^{-5}$ rad/s.

The training process is repeated fifteen times to minimise the influence of random factors. In each iteration, 70% of the data is randomly selected for training. Table I presents the average accuracy achieved by the six architectures, highlighting that AlexNet achieves the highest accuracy among them.

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