

In-situ Monitoring of Electrochemically Generated μm -sized Corrosion Pits Growth in Aluminum Thin Plates using Lamb Waves

Cyril Nicard, Marc Rébillat, Olivier Devos, Mohamed El May, Nazih Mechbal

Abstract. Corrosion is a major threat in the aeronautic industry, both in terms of safety and cost. Efficient and cost affordable solutions for corrosion monitoring are thus needed. Ultrasonic Lamb Waves (LW) are very efficient for corrosion monitoring and can be made cost effective and versatile if emitted and received by a sparse array of piezoelectric elements (PZT). A LW solution relying on a sparse PZT array and allowing to monitor μm -sized corrosion pit growth on aluminum thin plates is here proposed and evaluated. Experimentally, the corrosion pit size is electrochemically controlled by both the imposed electrical potential after a localized coating defect has been generated. In parallel, the corrosion pit growth is monitored in-situ every 10 seconds by sending and measuring LW using a sparse array of 4 PZTs bonded to the back of the aluminum thin plate enduring corrosion. As a ground truth information, the corrosion pit volume is estimated as the dissolved volume balancing the electronic charges exchanged during corrosion. Measured LW signals are then post-processed in order to compute a large collection of synthetic damage indexes (DIs). After dimension reduction steps, obtained DI values correlates extremely well with the corrosion pit radius. Using a linear model relating those DI values to corrosion pit radius, it is demonstrated that corrosion pits can be reliably detected and their upcoming size extrapolated. LW managed by a sparse PZT array thus appears to be reliable and efficient to monitor growth of μm -sized corrosion pits growth on aluminum thin plates.

Key words: ultrasonic guided waves, corrosion pit, structural health monitoring, aluminum

1 INTRODUCTION

Corrosion within metallic structures can render an aircraft un-airworthy by weakening structural components, roughening the outer surface, loosening fasteners, hastening cracking, and facilitating the entry of water into electronic fixtures. Anticipating corrosive conditions ahead of time can lead to significant cost savings and less aircraft downtime [1]. In order to limit corrosion issues, a typical aeronautic structure is made of qualified aluminium alloys protected from the environment by treating the surface with adequate coatings. It is generally expected that the protective surface is perfectly flawless over the whole structure. But on a large structure undergoing everyday service this cannot be the case. Impact damage during service life is a common occurrence of coating failure. Damage during maintenance (tools and split

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fluids) can also occur as well as paint cracking at high stress points around joints. From these initial premises, corrosion pits can start and threaten the integrity of the structure at a global level, thus motivating the need for in-situ pitting corrosion monitoring technologies.

Industrially speaking, an ideal corrosion monitoring technology should allow to monitor large-scale structures, to automate measurements, to detect corrosion pits from their premises, and to exhibit a high correlation between sensors measurements and the size and locations of corroded areas. Although various effective non-destructive testing (NDT) methods have been developed to monitor corrosion, they remain limited in their ability to detect and assess corrosion premises and to reliably size a given corrosion damage. Moving from planned maintenance to condition based maintenance (CBM), *i.e.* maintenance only when necessary, seems mandatory to solve these issues. Monitoring in real time and autonomously the health state of structures is thus of high interest in this context. Such a process is referred to as Structural Health Monitoring (SHM) [2, 3]. To achieve this goal, structures become “*smart*” in the sense that they are equipped with sensors, actuators, and algorithms that allow them to state autonomously regarding their own health. There is thus a real need for a large scale, automated, sensitive, low cost and embedded technology to develop corrosion monitoring SHM methodologies of aluminum aeronautic parts.

Ultrasonic technologies relying on Lamb Waves (LW) have been shown to be extremely sensitive to corrosion damage [4, 5] and can be easily automated thanks to permanently embedded piezoelectric elements (PZT) networks [6]. In the present work, the focus is thus put on corrosion monitoring methods based on LW and applied experimentally to plate-like structures. LW inspection methods based on sparse PZT transducers arrays are the most suitable from a practical point of view but have never been validated on small corrosion pits realistic of actual corrosion in aluminum ($\approx 10 \mu\text{m}$ in radius) but rather on large generalized corrosion areas (in cm). In a previous work, the authors demonstrated that such an approach is however possible for steel thin plates [7] and associated experimental data have been made available in open access online [8]. The purpose is here to extend this approach to aluminum thin plates.

An option to achieve localized corrosion on aluminium thin plate samples is to protect their surface with a varnish, coat, or paint and to artificially generate a small damage in the protective layer for the pit to develop under control electrochemistry. This method has thus been used here and adapted to fit requirements imposed by the simultaneous presence of a sparse PZT arrays managing LW emission and reception.

The objective of this paper is thus first to introduce an experimental setup allowing to control electrochemically the growth of a μm -sized corrosion pit on a coated aluminium thin plate sample and to simultaneously monitor it in situ by means of LW emitted and received using a sparse array of PZT transducers. It will secondly be demonstrated that such measurements can be post-processed to compute damage indexes (DIs) that, after dimension reduction, correlate very well with actual corrosion pit radius as estimated electrochemically and allow to predict its upcoming size.

3 ELECTROCHEMICALLY CONTROLLED μm -SIZED CORROSION PITS GENERATION AND IN SITU ULTRASONIC LAMB WAVES MONITORING

3.1 Experimental samples

The experimental specimen is a 1.5 mm thick aluminum plate with dimensions of 80 mm by 125 mm. Four PZT transducers (Noliac NCE51, $\text{Ø}10\text{ mm} \times 1\text{ mm}$) are bonded to the plate at specific geometrical positions, as shown in *Figure 1* [Left]. When selecting these positions, care was taken to break symmetry in the layout of the sparse array and to avoid placing the transducers too close to the plate edges in order to reduce Lamb wave reflections. Each transducer is connected to a 150 mm coaxial cable, which is brazed to the element to optimize the signal-to-noise ratio and allow for both the transmission and reception of Lamb waves. The PZTs are bonded to the plate following Cedrat Technologies' recommended bonding procedure. *Figure 1* [Right] shows the rear face of the aluminum plate. The front face (the one subject to corrosion) has been coated with an acrylic protective varnish (Electrolube), except for a 0.4 mm hole drilled at the center of the surface. This hole was manually created to locally damage the varnish while minimizing impact on the underlying aluminum.

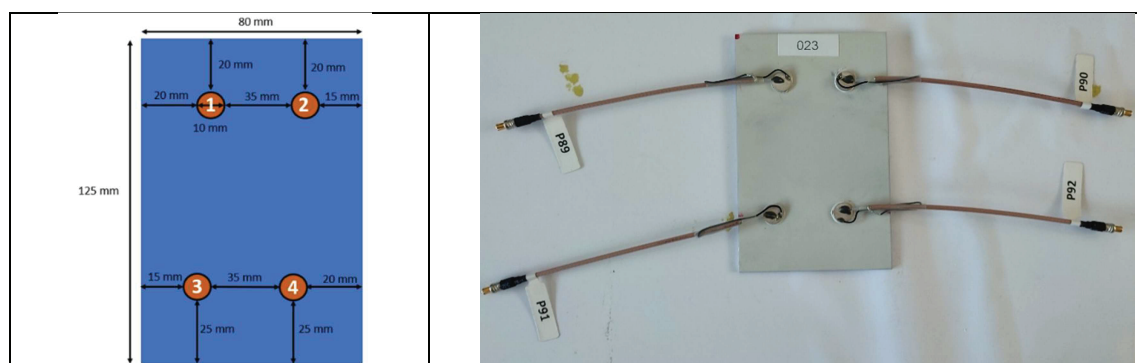


Figure 1: Experimental steel sample under study. [Left] Position of the PZTs composing the sparse network. [Right] Back face of the sample with the 4 bonded PZTs.

3.2 Electrochemical experimental setup

A dedicated electrochemical cell (see *Figure 2* [Left]) was designed and 3D printed using PETG filament for the purposes of the experiment. The cell measures 96 mm $\times$ 60 mm $\times$ 48 mm and holds approximately 150 mL of electrolyte. Its geometry also allows for direct optical microscopic observation of the steel surface using a Keyence VH-Z50L long working distance objective. An overview of the complete experimental setup, along with detailed components, is shown in *Figure 2* [Right].

To carry out the corrosion experiments, a standard three-electrode configuration is employed. The working electrode (WE) is the aluminium 2024 sample plate, the counter electrode (CE) is a 20 mm $\times$ 20 mm platinum wire mesh, and the reference electrode (RE) is a silver/silver chloride electrode (Ag/AgCl). The CE and RE are inserted into the cell from the top, while the aluminium sample (WE) is mounted at the bottom of the cell using an adaptor

and an O-ring. This setup ensures water tightness while avoiding any contact or mechanical stress on the PZT transducers. The electrodes are connected to a VersaSTAT 3F (Ametek) potentiostat, which manages the electrochemical control and measurements.

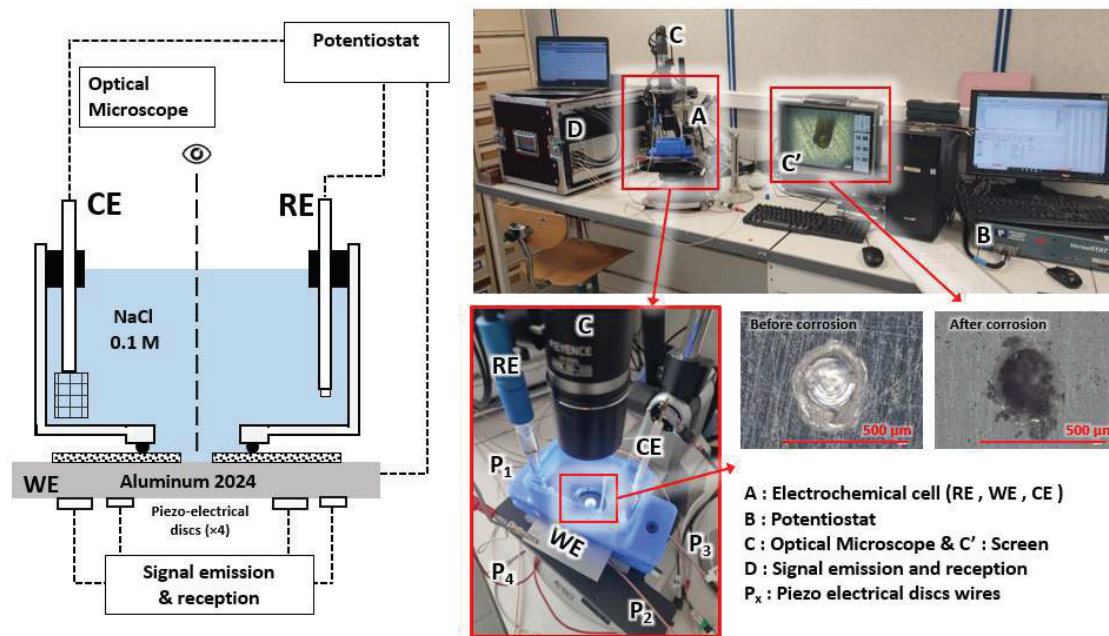


Figure 2: [Left] Schematic of experimental set up and [Right] Pictures of experimental setup with zooms on the specific equipment's details in the text.

3.3 Controlled generation of localized corrosion damage

To induce corrosion damage, preliminary experiments were conducted to determine the appropriate experimental conditions. The open-circuit potential (OCP) of our Aluminium 2024 sample was measured at -620 mV vs Ag/AgCl. Based on this, two different potentials were selected to induce corrosion damage: P1 = -700 mV vs Ag/AgCl, and P2 = -200 mV vs Ag/AgCl. These correspond to the passive and active dissolution regions, respectively, of Al 2024 in a 0.1 M NaCl solution.

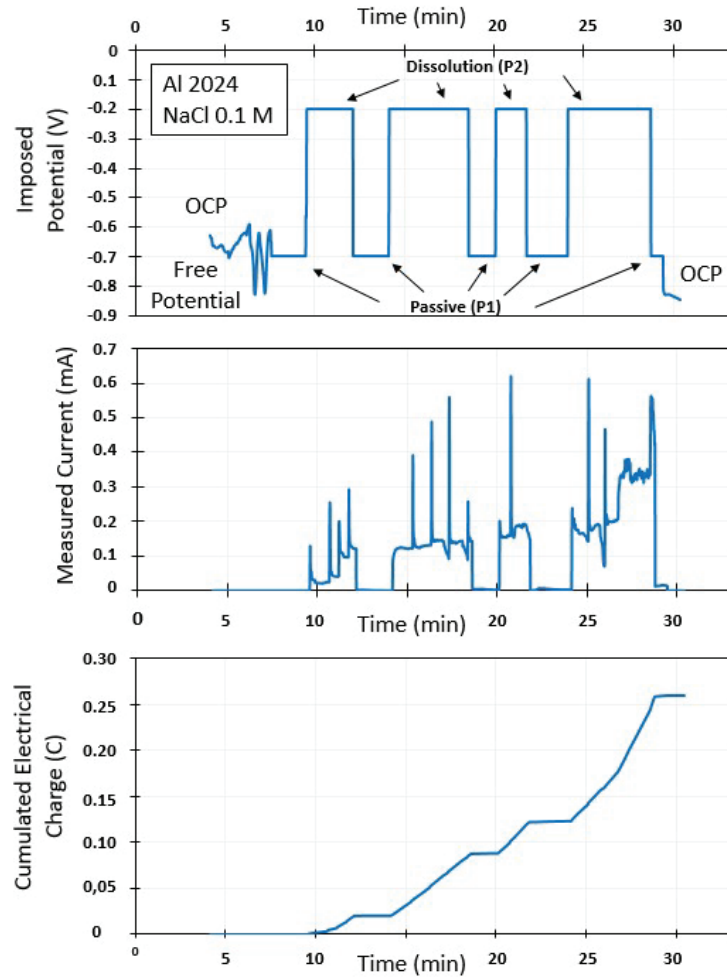


Figure 3: Experimental measurement for localised corrosion on Al 2024. Those figures display the imposed potential, measured current and cumulated electric charge.

To establish a relationship between the electrical charge exchanged during corrosion and the resulting damage size, a coefficient called the “dissolution ratio” D_r (in $\text{mm}^3 \cdot \text{C}^{-1}$) is defined as follows:

$$D_r = \frac{V}{Q} \quad \text{Eq. 1}$$

where V is the volume of the corrosion pit formed by the dissolution of aluminum, and Q is the total charge exchanged.

Preliminary tests revealed a linear relationship between the exchanged charge Q and the pit volume V , within our experimental range. This indicates that D_r can be considered a constant under the given conditions, regardless of the pit radius. The measured value is : $D_r = 20.1 \times 10^{-3} \text{ mm}^3 \cdot \text{C}^{-1}$.

Assuming a hemispherical shape for the corrosion pit, an estimate of the pit radius r_e can be obtained using the following equation:

$$r_e = \sqrt[3]{\frac{3QD_r}{2\pi}} \quad \text{Eq. 2}$$

where Q is the cumulative charge (in coulombs) measured over time. The evolution of radius along with time as computed from the measured cumulative charge is shown in *Figure 4*.

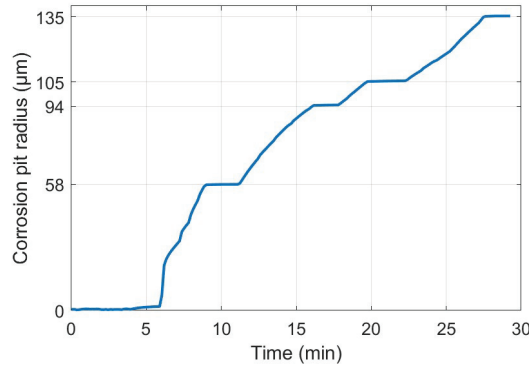


Figure 4: Corrosion pit radius evolution with time during the experiment calculated from cumulated charge in Figure 3.

3.4 In-situ ultrasonic Lamb waves measurements

During the corrosion experiment, LW are being emitted and received by the sparse array of 4 PZTs bonded at the back face of the aluminium sample (see *Figure 1* [Middle]). The system used for LW management is provided by Cedrat Technologies and can be seen in *Figure 5*.

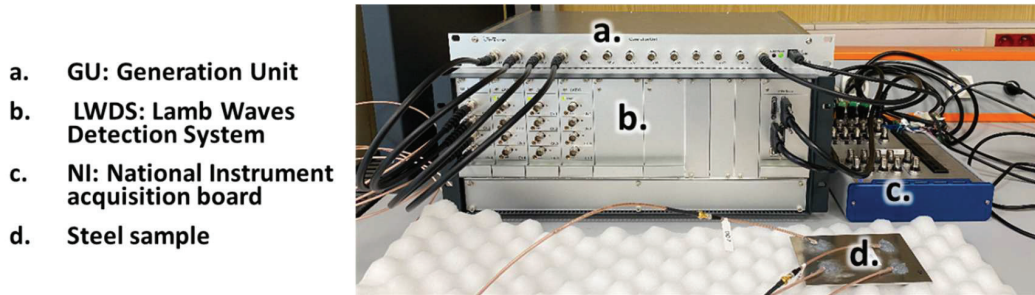


Figure 5: Overview of Cedrat Technologies LW management system.

The LW management system is made up of three blocks: the Generation Unit (GU) generates the signals to be sent for each channel and that can manage simultaneously up to 12 channels. The Lamb Waves Detection System (LWDS) can contain up to 16 independent channels. For each channel, the LWDS has a power amplifier ($\pm 15V$, 1A) allowing to drive the PZT with a bandwidth larger than 1MHz, and a switching system allowing to toggle between emitting (pulse mode) and receiving (echo mode). Resulting signals are then acquired with a 2 MHz sampling frequency by a National Instrument (NI) acquisition board. Here, only 4 channels of the GU, the LWDS and the NI systems are being used. A custom MATLAB script configures

in a round robin fashion one PZT in actuator mode (pulse mode) and the three others in sensing mode (echo mode) before performing the acquisition. The PZT in pulse mode will generate a Lamb wave at a central frequency of 200 kHz and the other ones will receive the resulting LW that will then be measured by the NI interface. The time required to collect (≈ 50 ms) and store (≈ 9.5 s) the signals for the 4 PZT is around 10 seconds. Measurements are run constantly during the corrosion process and thus one measurement is available roughly every 10 seconds during the corrosion pits growth. Precise time stamps associated with each measurement are also stored.

4 DAMAGE SIZE ESTIMATION FROM LAMB WAVES MEASUREMENTS

4.1 Denoising of raw Lamb waves signals

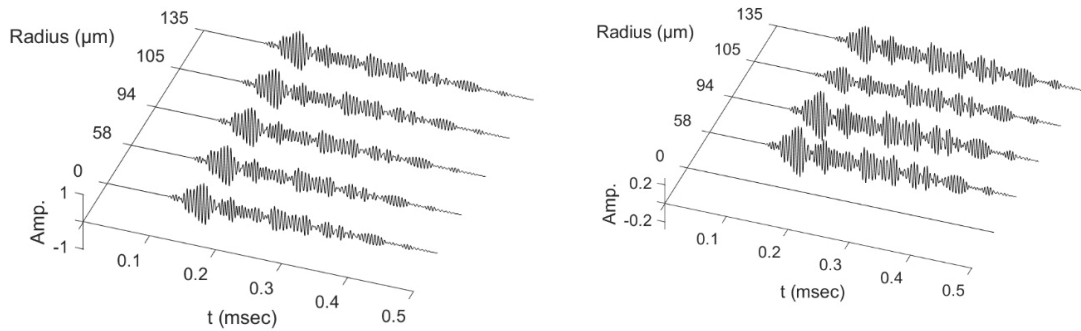


Figure 6: Example of LW signals measured on the path going from PZT 1 (actuator) to PZT 2 (sensor) for the first [left], and the difference between damaged signals and the reference one [right] for various radius of corrosion pits.

As pre-processing steps, the measured LW signals are first denoised by means of a discrete wavelet transform up to the order 4 using the “*db40*” wavelet. Those signals are then filtered around their excitation frequency $f_0 = 200$ kHz using a continuous wavelet transformation based on “*morlet*” wavelets and with a scale resolution equal to 20. The objective of this pre-processing step is to perform a band pass filtering around the excitation frequency by means of wavelets in order to limit the influence of experimental noise. The scale parameter can be sought as an image of the bandwidth of the retained bandpass filter over the frequency range of interest. The diaphonic part present in the measured signals (*i.e.* the copy of the input signals that appears on the measured signal due to electromagnetic couplings in wires) has been eliminated based on the knowledge of the geometrical positions of the PZT and of the estimated waves propagation speed in the material.

Examples of LW signals measured on the path going from PZT 1 (actuator) to PZT 2 (sensor) (see Figure 1 [left]) for various radius of the corrosion pits are shown in Figure 6. The differences between the Lamb waves signals collected in the healthy condition (with a radius equals to 0 μm) and the ones collected at various corrosion states (with a radius larger than 0 μm) are also shown. This confirms that the diffraction generated signals are of small amplitude,

but still exists and can be experimentally observed.

4.2 Damage indexes computation

After LW signals have been denoised for all available actuator-sensor paths, signals are compared together one by one through the computation of a set of 40 Damage Indexes (DI) that have been previously designed for damage monitoring purposes using LWs [9]. These DIs can be categorized depending on the feature of the signal that they target to describe (energy, amplitude, time of flight, or statistical properties among others). One DI is computed from two signals that one would like to compare. Typically one signal in a healthy or reference state is compared to another in a damage state. However, as it has been previously shown, the signals due to the corrosion pit may be of small amplitude and thus corrupted by noise. In order to mitigate that issue, Lamb waves measurements are repeated several times when it is possible (here in the healthy reference state and when the injection is stopped and thus the corrosion pit radius steady). Consequently, instead of having one value of a DI, several values associated with its probability density function are available. Illustrative DIs histograms (namely cross-correlation [CC] and standard deviation [STD]) for the reference and corrosion cases corresponding to intermediary corrosion pits radius values for the path "Actuator 1 - Sensor 3" are plotted in *Figure 7*. From this figure it can be seen that irrespectively to the considered experiment or to the considered DI, a global increase is observed along with the corrosion pit radius growth. Furthermore, it can also be seen that the DIs distribution for a given case is relatively spread around its mean value meaning that the effect of noise is somewhat important here and should be considered. This is in agreement with the previously observed small effect of corrosion pits on the measured LW signals. This furthermore demonstrates the effective experimental sensibility of the LW based proposed approach to μm -sized corrosion pits.

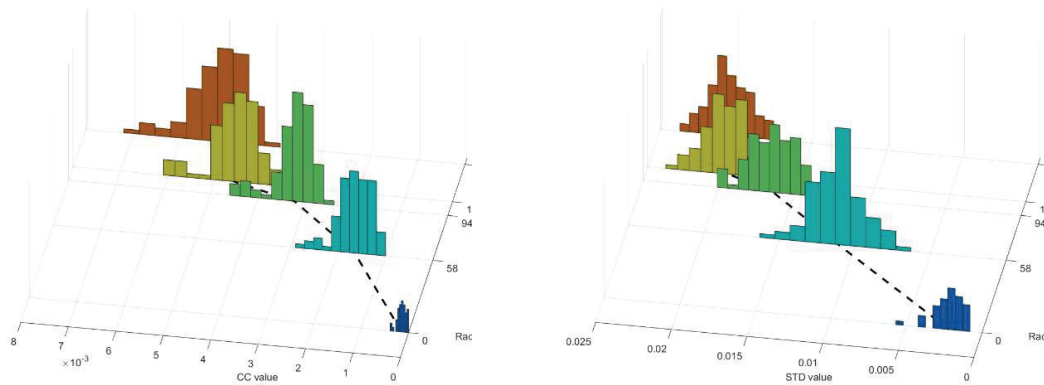


Figure 7: Example of the evolutions with corrosion radius size of DIs computed for the first experiment : [Left] CC and [Right] STD for the path PZT 1 to PZT 3.

A second way to compute DIs consists in processing incoming LW measurements acquired sequentially each ≈ 10 s and not to group them as previously by constant corrosion pit radius values. A first measurement is taken as a reference and then all the upcoming measurements are compared to this reference one and associated DIs computed. In that case, the obtained DIs

thus constitute temporal series evolving with time along with the damage radius. The correlation of some DIs (namely cross-correlation [CC] and standard deviation [STD]) with corrosion pit radius for the path "Actuator 1 - Sensor 3" are plotted on *Figure 8*. The plateaus associated with each state corresponding to a stop in the corrosion process can clearly be seen on this figure. The correlation quality between the DIs and the corrosion pit radius can be evaluated using the R^2 coefficient denoting the goodness of fit: a value close to one indicates a very good correlation and a value close to zero a very bad one. From this figure, it can thus be seen that whatever the considered DIs, an excellent correlation between DI values and corrosion pit radius is observed.

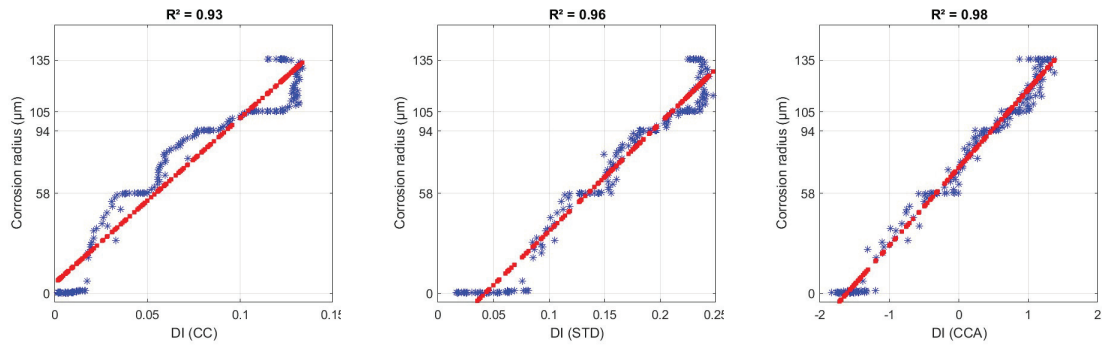


Figure 8: Example of the correlation with corrosion radius size of DIs CC [Left] and STD [Middle] and optimized DIs CCA [Right] for the path PZT 1 to PZT 3.

4.3 Dimension reduction

It is then necessary to be able to reduce the dimension of this set of informative DIs in order to filter out as many variability effects as possible and to keep the most information possible regarding corrosion pit sizes. As a first dimension reduction step, the DIs are averaged spatially for all paths available over the structure to be monitored. What has been chosen here is just to sum out the damage indexes obtained for all the paths in order to obtain 40 global damage indexes denoted DI_G . As a second dimension reduction step, the 40 DI_G that have been computed previously can be processed in order to compute a single DI being the most informative possible. In order to achieve this goal, Canonical Correlation Analysis (CCA) [10, 11, 12] that seek for a lower dimensional space optimizing discrimination has been retained. The CCA approach looks for the linear combination of DIs that maximizes the correlation between projected input and output data. In this way, CCA can conveniently deal with directions of the input or output spaces that present very high correlation. Consequently, after spatially integrating data over the whole structure, a second dimension reduction operation is achieved from a DI space having 40 dimensions to a reduced mono-dimensional space using CCA and makes use of both the 40 DI_G and the corresponding corrosion pit sizes (as CCA is a supervised method) for learning. The optimal DI computed using spatial aggregation and CCA is plotted in *Figure 8* [Right] and it can be seen that such a dimension reduction step indeed increases the correlation between DIs and corrosion pit radius.

4.4 Damage size extrapolation

Finally, the last step of the SHM process investigated here consists in being able to quantify corrosion pits size given only the measured LW signals or equivalently the DIs after the reduction dimension steps. What is more precisely targeted here is to achieve corrosion pits size extrapolation, *i.e.* to predict upcoming larger corrosion pit damage size on the basis of information acquired only on smaller corrosion pits. It is a two steps extrapolation process. As a first step, a linear model relating the corrosion pit radius to the reduced dimension DI is being learnt. This linear model is learnt only from small damage radii. Then, during the extrapolation step, DIs are computed for signals measured with larger values of corrosion radii. Finally, by inverting the linear model relating the DI value with the corrosion pit radii, it is then possible to infer the actual damage radii from the reduced dimension DI and thus to predict it. More details regarding those steps are provided in the following.

In practice, according to the linear correlation demonstrated between the reduced dimension DI and the corrosion pit radius, a linear model relating the reduced dimension $DI(r)$ to the actual damage size r is first learnt only on small damages with radii lying between 0 and r_{min} :

$$DI(r) = \mu_0 + \alpha r, \quad r \in [0, r_{min}] \quad \text{Eq. 3}$$

The estimated corrosion pit damage size $\hat{r}$ is then computed from $DI(r)$ by inverting the previously learnt linear model for larger corrosion pit radii lying between r_{min} and r_{max} as follows:

$$\hat{r} = \frac{DI(r) - \mu_0}{\alpha}, \quad r \in [r_{min}, r_{max}] \quad \text{Eq. 4}$$

The only parameter in that corrosion pit size extrapolation method is related with the range of radii $[0, r_{min}]$ used for learning and can be set up as a percentage value of r_{max} . In order to filter out rapid estimation variations, estimated radii are averaged over 3 values (*i.e.* over 30 seconds) using a moving average algorithm. It should be noticed that performing extrapolation is particularly challenging and that classically damage quantification algorithms encountered in SHM only perform interpolation, *i.e.* damage size prediction inside the range where the learning phase has been achieved [13].

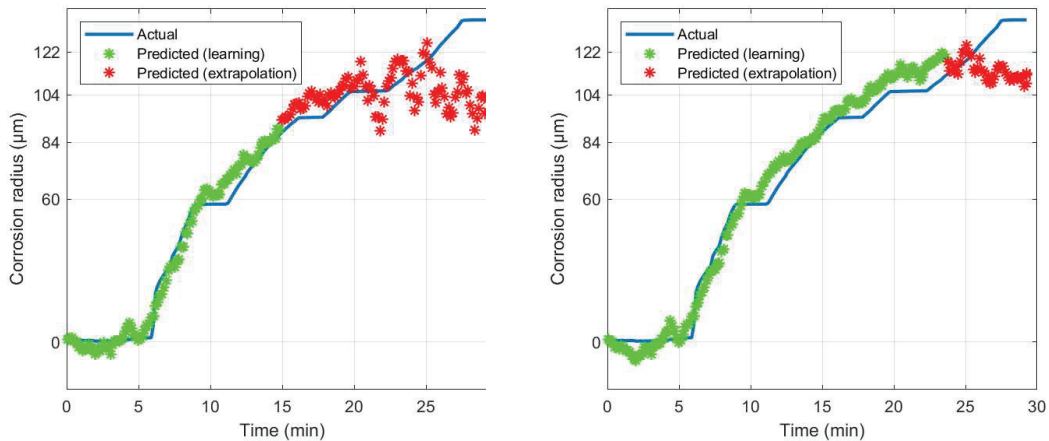


Figure 9: Corrosion pit radius extrapolation for the first experiment and for various learning rates (50% [left] and 80% [right])

Results of corrosion pit radius extrapolation for the first and second experiments and for various learning rates of 50% and 80% are shown in *Figure 9*. It can be seen that whatever the selected learning rate, the learning is correctly achieved (i.e. the green dots are lying close to the blue line) but the extrapolation has a tendency to underestimate the actual corrosion pit radius. This tendency for overestimation remains even when the learning rate is increasing. In conclusion, it can be stated that obtained results are always satisfying in the learning phase and that in the extrapolation phase results are conservative. Nevertheless, such results remains acceptable in practice from an industrial perspective. In terms of maintenance, what is interesting here is to be able to learn DI evolution from small corrosion pit damages that do not impart safety, and from this learning to be able to issue a warning signal when the monitored damage crosses a predefined safety threshold.

5 CONCLUSION

Corrosion is a major threat in the aeronautic industry, both in terms of safety and cost. Efficient, versatile, and cost affordable solutions for corrosion monitoring are thus needed. Ultrasonic Lamb Waves (LW) appear as very efficient for corrosion monitoring and can be made cost effective and versatile if emitted and received by a sparse array of piezoelectric elements (PZT). A LW solution relying on a sparse PZT array and allowing to monitor μm -sized corrosion pit growth on aluminium thin plate is here evaluated. Experimentally, the corrosion pit size is electrochemically controlled by both the imposed electrical potential after locally damaging the coating at the desired pit location. In parallel, the corrosion pit growth is monitored in-situ every 10 seconds by sending and measuring LW using a sparse array of 4 PZTs bonded to the back of the steel plate enduring corrosion. As a ground truth information, the corrosion pit volume is estimated as the dissolved volume balancing the electronic charges exchanged during corrosion. Measured LW signals are then post-processed in order to compute a collection of synthetic damage indexes (DIs). After dimension reduction steps, obtained DI values correlates extremely well with the corrosion pit radius. Using a linear model relating those DI values to corrosion pit radius, it is demonstrated that for corrosion pit from $30\ \mu\text{m}$ to $150\ \mu\text{m}$, their upcoming size can be extrapolated in a conservative manner. LW managed by a sparse PZT array thus appears to be reliable and efficient to monitor growth of μm -sized corrosion pits on aluminium plates. If embedded in aeronautical structure, such an approach could be a versatile and cost-effective alternative to actual non-destructive maintenance procedures that are both time and manpower consuming.

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