Automated analysis of Baffle Bolts

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Abstract

The Baffle bolts (BB) are components of the lower internals of the vessel of Pressurized Water Reactor (PWR) nuclear power plants. They are subjected to ultrasonic testing (UT) inspection as part of the Long-Term Operation (LTO) of the PWR plants worldwide. Unlike other areas undergo inspection, usually there are more than one thousand bolts in a typical PWR reactor.

The goal of the paper is to present how the Artificial Intelligence (AI) can be integrated into the inspection of the baffle bolts described in the introduction of the present document. The scope of the project was limited to the analysis of the signals acquired during the inspection to discriminate between healthy BB and those showing signals that need to be evaluated by an expert.

Some different independent algorithms are used by the automated analysis system, which counts with a support decision system to achieve the most robust result possible. First inspection of its kind was carried out in winter 2021 with promising results, being scheduled the next one in Fall 2022. The expectation is to get the system qualified according to the criteria stablished by the normative.

AI can be applied to UT inspections being the major limitation the amount of data, in a dual sense: train the data needed for the algorithms and obtain a confident improvement of the productivity. A key point of the project has been to create working teams of professionals that bring together knowledge in UT and AI.

1. Introduction

MRP-228, Rev.4: “Materials Reliability Program: Inspection Standard for Pressurized Water Reactor Internals—2020 Update”[1] stablishes the requirements for the Long-Term Operation for the internals of PWR type plants.

The Baffle Bolts, as part of the internals, are required to be volumetrically examined by means of Ultrasonic Testing. The geometry of these components differs among the different RPV (Reactor Pressure Vessels) technology and a given specific reactor, being the position and function of each type of Bolt different as well. Based on the location can be distinguished: Baffle to Former bolts and Barrel to Former bolts. There is other type of bolts as the Baffle edge bolts that are not included into the scope of this examination by ultrasonics.

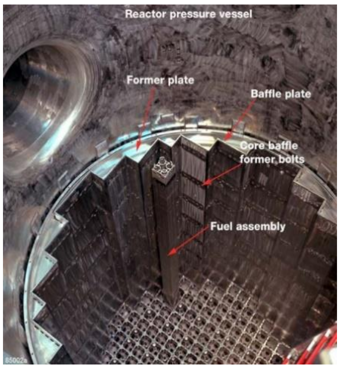

Figure 1: Vessel structure

Tecnatom has developed phase array UT techniques (PAUT) which meet the MRP-228 requirements for the Spanish fleet of Westinghouse type RPVs. Dimensions and specific configurations of these bolts on the baffle plates are considered as Westinghouse property information. The potential defects in the Baffle Former Bolts are postulated as IASCC and fatigue defects, being generated in three sensitive locations: Head to shank interface, first part of the shank and first part of the thread, as indicated in the figures below.

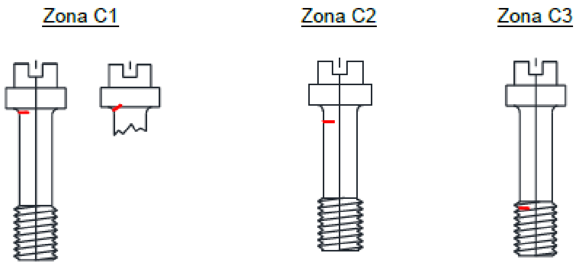

Figure 2: Postulated defect zones

The inspection procedure has been qualified according to UNESA CEX-120, "Methodology for the validation of NDT for the In-Service Inspection in Spanish NPP"[2] which is based on ENIQ requirements. The technique includes the use of Matrix Phase Array probe in Pitch & Catch and Pulse-Echo configuration.

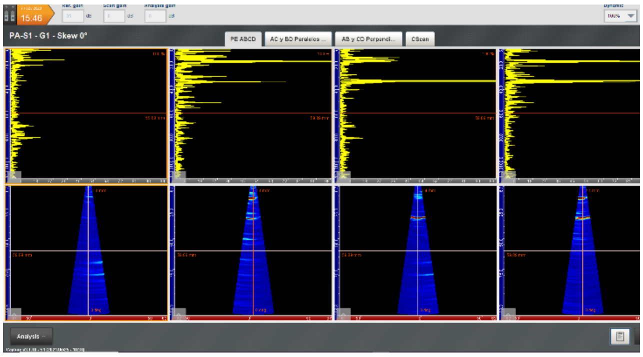
Figure 3: Software for Phased Array analysis

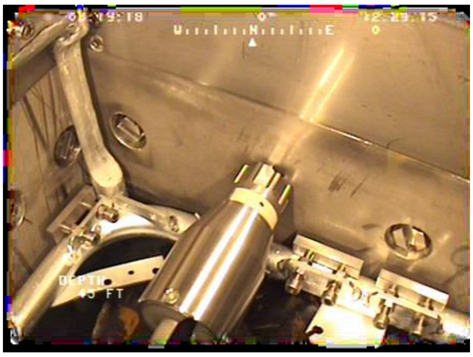
Figure 4: Baffle Bolt analysis

Given the number of specimens to be examined in a RPV (approximately one thousand depending on the RPV) in comparation to other components required to be inspected by means of UT in the nuclear field and the technological advances in the artificial intelligence, the question to be answered is: Would it be possible to design an algorithm capable of helping to analyst significantly to improve the productivity and the reliability of the inspection?

2. Goal of the paper

The goal of the paper is to present how the AI can be integrated into the inspection of the baffle bolts described in the introduction of the present paper. The scope of the project was limited to the analysis of the signals acquired during the inspection to discriminate between healthy BB and those showing signals that need to be evaluated by an expert.

3. Work performed

The work performed deal with data science development, in the sense that, the objective is to train an AI model for the detection of indications in Baffle Bolts acquisitions. Under this scheme, the tasks can be defined under the CRISP-DM[3], an open standard process that describes common approaches used by data science experts.

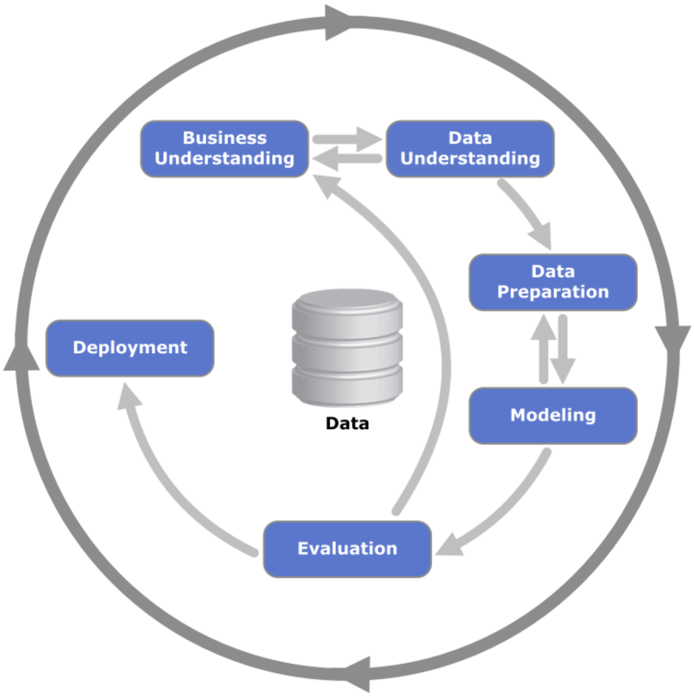

Figure 5: Project development phases

3.1. Data

The data used have several origins, which provides, on the one hand, an extra difficulty and, on the other hand, a greater guarantee when looking for general solutions. They mainly come from the inspection carried out at the nuclear power plant Almaraz 2 in 2022 and from acquisitions made on Baffle Bolts mock-ups with known defects, throughout the development of the technique. In any case, the data of Baffle Bolts with defects are still considered scarce and therefore the results obtained to date are not definitive.

Table 1. Available data

Origin	Number of data sane	Number of data non-sane
Demo at Spanish NPP 1	52	13
Inspection at NPP1	806*	9
Open mock-ups	7	3

** Some of them, with no defects, are filtered out as acquisitions with questionable signals*

3.2. Business understanding

The inspection procedure defines the acquisition and the analysis process to be followed. From the data science perspective are considered as relevant the aspects stated bellow:

- Pulse emission-reception mode, which include pulse-echo and pitch and catch modes.
- Criteria for the acceptance of the acquisition
- Location, size, and shape of the postulated defects
- Characterization of the signal

Some important considerations are:

- The background experiences and trainings of data scientists and NDT inspectors are significantly different, making it crucial to form mixed and well-integrated teams
- The context of real inspections is subject to improvements and changes in procedures, which can affect the data. The AI models require consistent input patterns for comparison and evaluation of new files.

3.3. Data understanding

Once the data available are identified, cleaned, and labelled and the procedure is understood, the next step is tackled, in order to be able to subsequently use Machine Learning techniques, the numerical arrays corresponding to each of the degrees of the different visuals used to explore the state of the BB.

A code had to be developed to extract the acquisition data from the original files: both the ultrasonic signal expressed in numerical data, as well as other data related to the technique. These arrays are a representation of each scanned degree of the bolt without making the focal law correction typical of Phased Arrays.

Figure 6: Three types of Baffle Bolts: BB2, BB1 and BB1 (from left to right)

From the beginning, one of the main problems was the lack of homogeneity in the data. Since the technique was optimized, some aspects of the acquisitions changed. This directly affected the data preparation since one of the premises for automatic learning is consistency in the input data. Once the previous problem was solved and filtered, a point was reached where the data obtained were unbalanced: many healthy bolt data versus very few defective bolt data.

In turn, there were several reasons why inspection data were discarded:

- Invalid data according to analyst: data that the analyst felt were acquired incorrectly or had stylus offsets that prevented correct interpretation.
- Data acquired with non-compatible configurations: a configuration was used on the probes that does not make the arrays compatible with the other training data.

- Incomplete data: data starting too late or not finishing the recording.
- Change in procedure calibration: incorrect calibration or calibration adapted to a specific bolt that affects data acquisition.
- Acquisitions with non-postulated defects: acquisitions that despite having some defects are of old bolts and with defects that it is no longer possible for them to appear due to the new structure of the Baffle Bolts.

Finally, a consistent data set was formed, with compatible acquisitions made with the same configuration (or one that could be adapted by SW).

The final dataset has a population of bolts labelled as healthy, ill-acquired healthy (that is consider as defective) and as defective.

3.4. Data preparation

Prior to training, it was necessary to ensure that all files were equivalent and standardized according to a pattern. Depending on the acquisition configuration, it was found that the acquisitions started at one millimetre or another. Since the data were initially read with the same initial offset, the signals of interest were displaced. The way to manage these differences in the screws was normalized in initial offset, in length (number of samples of each UT shot) and in amplitude. After performing this procedure, it was found that, indeed, as can be seen in the example of the following figure, if we superimpose the ASCAN signals at a specific angle, we find a defined pattern:

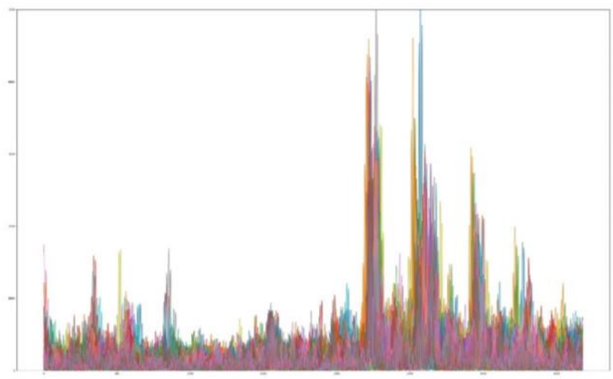

Figure 7: signal superimposition of several baffle bolt signals on the same channel

Once this was done, all the Baffle Bolt samples were trimmed to the same number of samples to homogenize them and cut the final parts that did not provide useful information.

3.5. Modelling

There are three different modalities of machine learning: unsupervised, supervised and reinforcement learning. In this case, the chosen modality is supervised learning, therefore the data are labelled prior to the training of the model.

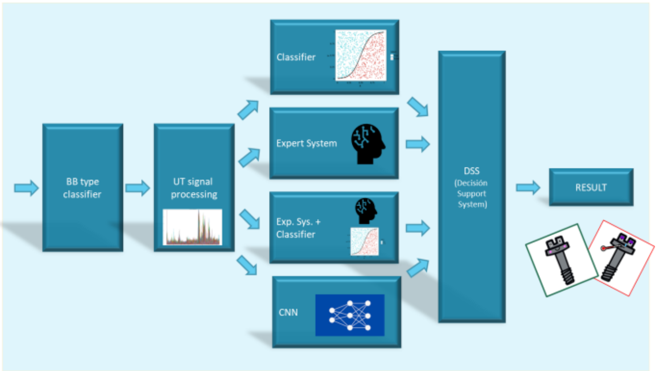

Figure 8: Automated analysis process from start to result

For a more accurate result a strategy of ensemble learning was used. Combining different techniques, a binary result was obtained for each screw health prediction method, in this case three methods, where "1" was a defective result and "0" was a result equivalent to a healthy screw. Once these three results were obtained, the statistical mode was chosen as the parameter to determine the condition of the screw.

The result is based on the DSS (Decision Support System), which is precisely this result product of the three methods listed below to evaluate the signals of the bolt:

- The expert System
- Machine learning classifiers
- CNN. Convolutional Neural Networks

3.5.1. Expert System

An expert system is defined as one of the applications of Artificial Intelligence in which a machine imitates human behaviour when performing a certain task, in this case the evaluation of Baffle Bolts. To build it, we talked to ultrasonic inspection analysts and designed a logic with the steps they would follow to determine if a Baffle Bolt is healthy or with a possible defect.

After a period of investigation, we set up a series of filters with defined thresholds to detect the existence of known relevant signals. Some of them are defect-related signals and some of them are signals to be distinguished in healthy baffle bolts. Some of these signals are: geometrical echoes of the screw, bottom echoes or crack echoes.

This is how, for example, the bottom echo window would look in one of the channels (in this case, the minimum amplitude and the position (with tolerance) in which this signal must be found are known.):

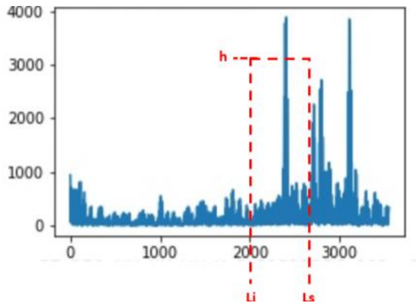

Figure 9: A gate configured to find desired signal

For the classification by means of the defined filters, a logic is configured according to the previously explained criteria. The advantage of this method is its robustness, however it is very inflexible and does not learn from the data but simply validates itself with them.

In the below-left figure, it is displayed a healthy signal by detecting signals in the blue square, where in the below-right, it is displayed an unhealthy signal by detecting signals in the pink square.

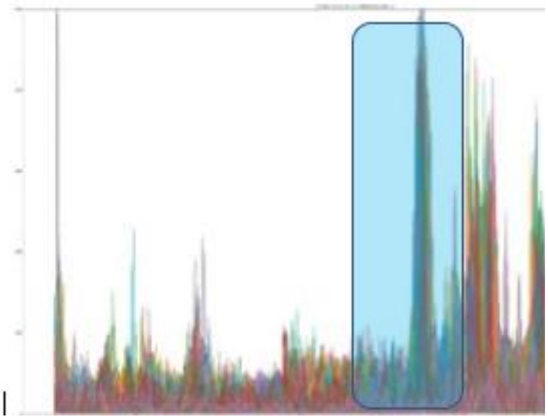

Figure 10: a window to find healthy signals

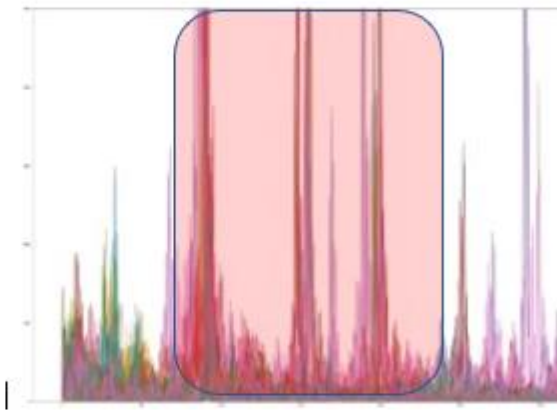

Figure 11: a window to find unhealthy signals

3.5.2. Feature vector.

Taking advantage of part of the information obtained with the filters of the expert system, a vector of characteristics was defined, where the participating signals were assigned 1 or 0 depending on whether they were detected or not. Subsequently, this vector, which was initially composed of 12 values, was introduced in a machine learning process, where different classifiers learned to distinguish which characteristics were usually related to healthy BBs and which were related to defective BBs. This strategy combines some advantages of the expert system (we guide the data where to learn from) with those of machine learning where it is able to generalize results by finding non-trivial patterns. By analysing these filters in both the intermediate pulses and the bottom echo, it has obtained vectors for each Baffle Bolt that are evaluated in two ways: defect or healthy candidate.

For example, in an expert system using 12 filters, a possible training vector would be:

Feature Vector: { 1,1,1,1,0,1,0,1,0,1,0,0}

Figure 12: a features vector example

3.5.3. Machine learning classifiers

This classifier analyses arrays representing an entire scan using all channels and grades of each Baffle Bolt: all available signals from the phase array are used, so that the algorithms themselves learn the patterns of the data.

To analyse these data, the signals are normalized to work on the same basis, the dimensionality of the data is reduced, the noise that prevents to see the most relevant signals is filtered and later the results are binarized, leaving us with a 1 in the most relevant signals and a zero in the less relevant ones.

The working order would be as follows:

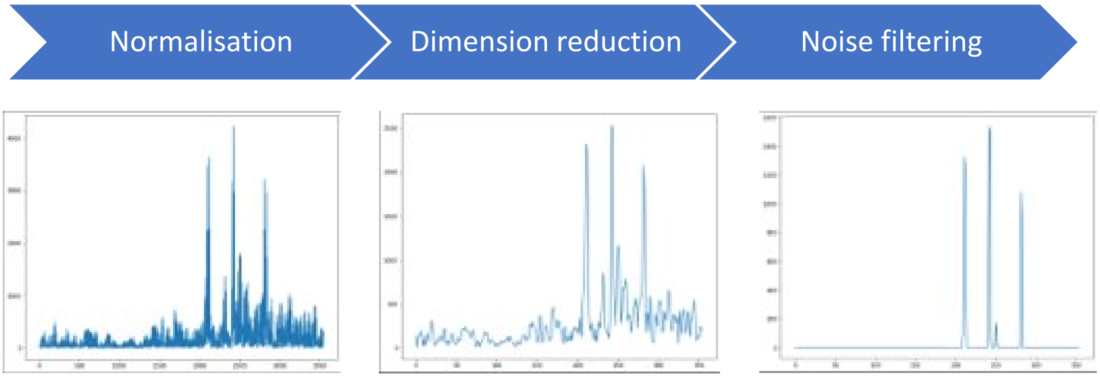

Figure 13: Preprocessing of signals to apply our channel classifier

To ensure a better result different classifiers have been explored, comparing their performance to find the one with the best balance between classification accuracy and no (or close to zero) false negatives.

3.5.4. Convolutional Neural Network

Convolutional Neural Networks (ConvNets or CNNs) are a class of deep neural networks, most applied to analysing visual imagery. They are designed to learn hierarchical feature representations automatically and adaptively from input data, through repeated use of convolutional and pooling layers. These architectures are particularly useful for image classification and recognition tasks, as they are capable of extracting features from images and learn relationships between image features and the target classes.

Currently, the use of neural networks has been added to the methods used to obtain the Ensemble, still to be tested with new acquisitions to be made soon.

In this method, image processing techniques are used to take advantage of the scans obtained when acquiring the signal of each bolt.

C-SCAN of all channels are merged to form a single 256x256 pixel image, as shown in the following figure:

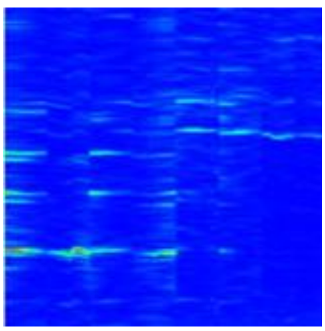

Figure 14: all channels merged and processed as an image to be provided a feed to a cnn

The problems encountered when using the CNN have been that due to the size of the dataset it still does not achieve very good results in tests, while the trainings it learns them too well, which is known as an overfit.

3.6. Evaluation

The matrices shown above are the result of testing the algorithms on the training data. 0 and 1 are equivalent to healthy and defective respectively, with the real data on the vertical axis of the graph and the data predicted by the system on the horizontal axis.

As can be seen, the prediction was very effective, although we show the first results training only with mock-up data. However, when it came to inspection, the trained algorithms were inconclusive, as the actual acquisitions had notable differences.

This is due to the fact that the procedure used in the inspection was different from the one used for the training data, being much stricter than the one actually applied in the real inspection.

Following these results, it was proposed to change the procedure for the inspection carried out in 2022.

The algorithms were retrained with the updated rules and new training data were added. After this training, the different prediction systems were retested, in spite of the previous difficulties to obtain a large amount of training data and that they were correctly acquired.

The most recent results obtained with the updated algorithms applied on real data, although still preliminary, provide an **accuracy of between 80% and 98.5%**. Even the results are still very good, the goal is to reduce false positives (bolts that are actually defective and are classified as healthy) to zero as these screws are the ones that can be dangerous for nuclear safety to be misclassified.

3.7. Deployment

An on-premises application was developed that applied the models already trained by the Data Science team to each acquisition to facilitate the task to the analyst team.

This application is designed to be an inspection support tool with three main objectives:

- Display and manage the automatic evaluation.
- Allow interaction with the analysts.
- Generate automatically inspection reports.

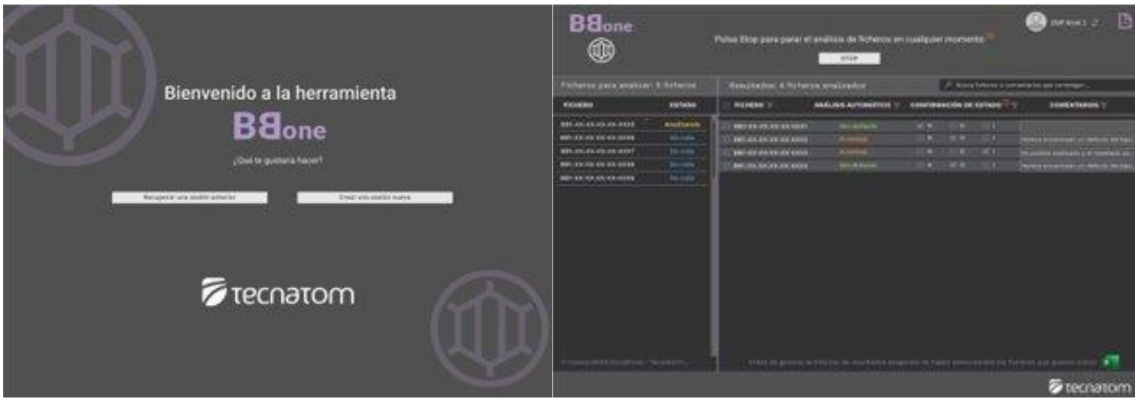

Figure 18 BBOne application

4. Conclusions

AI can be applied to UT inspections being the major limitation the amount of data, in a dual sense: train the data needed for the algorithms and obtain a confident improvement of the productivity.

One of the first lessons to keep in mind is the importance of having the ultrasonic technique well defined from the beginning. Having data acquired in a uniform and consistent manner over time will ensure the compatibility of developments both backwards and forwards. So, the UT signals are the base of the data and have a strong influence in the performance of the AI algorithms.

In addition to data consistency, having a large, varied, and balanced set is also a major effort. By the nature of these inspections, data are strongly unbalanced in the nuclear field. So different alternatives have to be found to make up for this problem: many acquisitions in mock-ups, data augmentation..etc

Other issue to have in mind is that no matter how good the mock-ups are, inspections under real conditions always bring new challenges. In this case, the signals acquired from real Baffle Bolts were noisier, attenuated and with new echoes to be evaluated. This knowledge must be transferred to the models after the first experiences, which is always a difficulty.

With safety as a priority, this project aims to achieve through AI an improvement in the performance of baffle bolt inspections. As it is proposed, by reducing the number of acquisitions to be evaluated as much as possible, several objectives are reached:

- Reduce analysis time in the “critical path” refuelling outages.
- To reduce the number of analysts and therefore the cost of the inspection.
- Ensure that analysts focus on evaluating "extraneous" or potentially defective records.

This, on the other hand, minimizes human error since in an inspection the percentage of "dangerous" records is very small and can be masked.
Tecnatom is currently in an intermediate phase of the project. We have already accumulated the experience of confronting the algorithms to the real world, which allows us to adjust the next steps to consolidate a viable and robust solution.

5. References

1. MRP-228, Rev.4: “Materials Reliability Program: Inspection Standard for Pressurized Water Reactor Internals—2020 Update”, EPRI Technical Update, December 2020
2. UNESA CEX-120, “Methodology for the validation of NDT for the In-Service Inspection in Spanish NPP”, 2003
3. CRISP-DM 1.0. Step-by-step data mining guide, Pete Chapman (NCR), Julian Clinton (SPSS), Randy Kerber (NCR), Thomas Khabaza (SPSS), Thomas Reinartz (DaimlerChrysler), Colin Shearer (SPSS) and Rüdiger Wirth (DaimlerChrysler)