DIPARTIMENTO di INGEGNERIA

LA RICERCA DENTRO UNIME

Safety management of atmospheric storage tanks by the modeling of bottom corrosion

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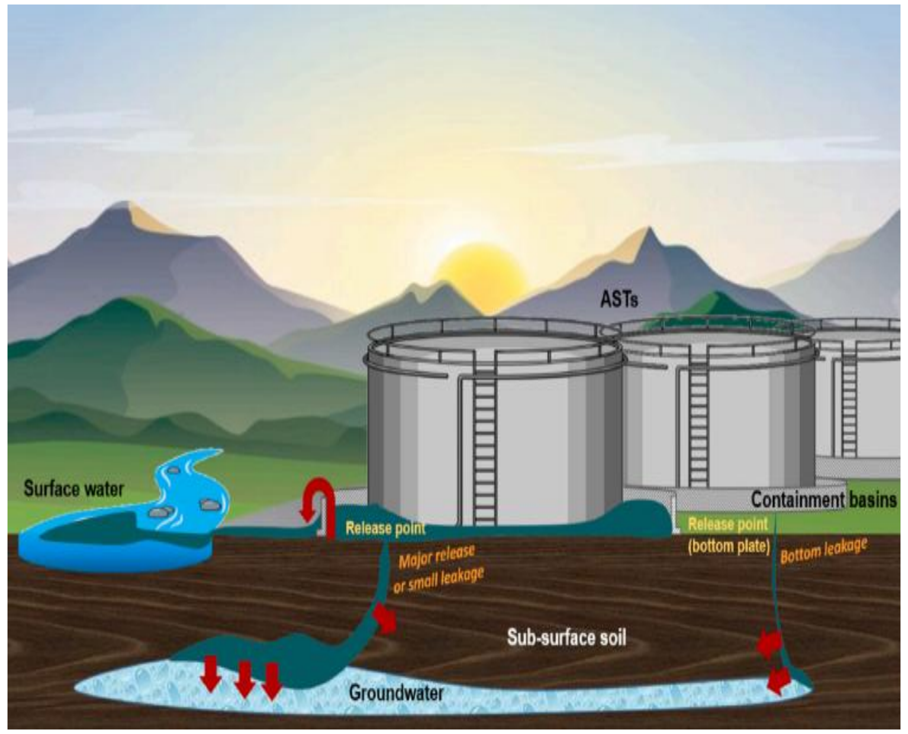
Corrosion in atmospheric storage tanks (AST)

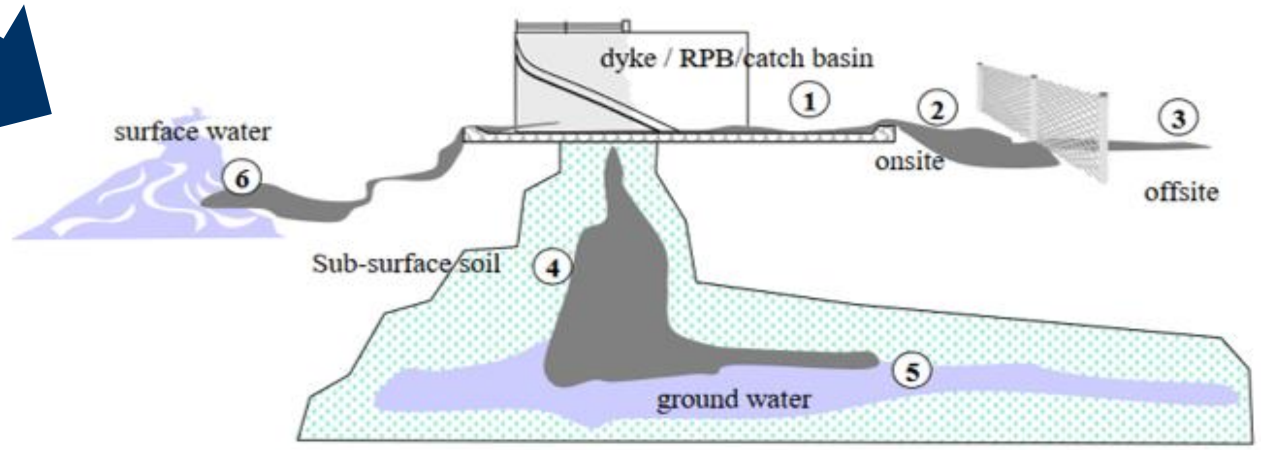
Corrosion is a critical issue of atmospheric storage tanks, often it is the cause of fuel releases with serious consequences for humans and the environment.

Examples of storage tanks damaged by localized corrosion



Fuel Release

Pool fire



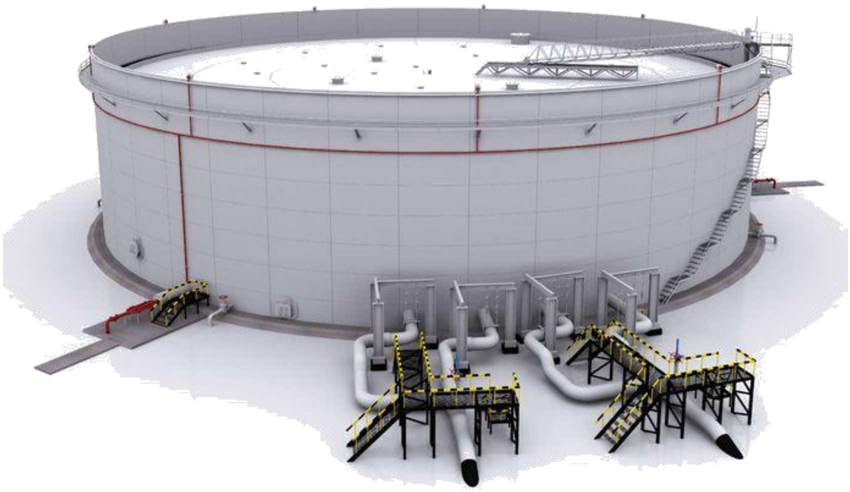
Ground water contamination

API Standard 653 - Tank Inspection, Repair, Alteration and Reconsruction, Third Edition.
Giusi Ancione, P. B. (2023). Tecniche avanzate per la gestione dei serbatoi di stoccaggio atmosferico. Roma: Inail.
Sandia National Laboratories. (s.d.). Validation and Qualification Sciences Experimental Complex

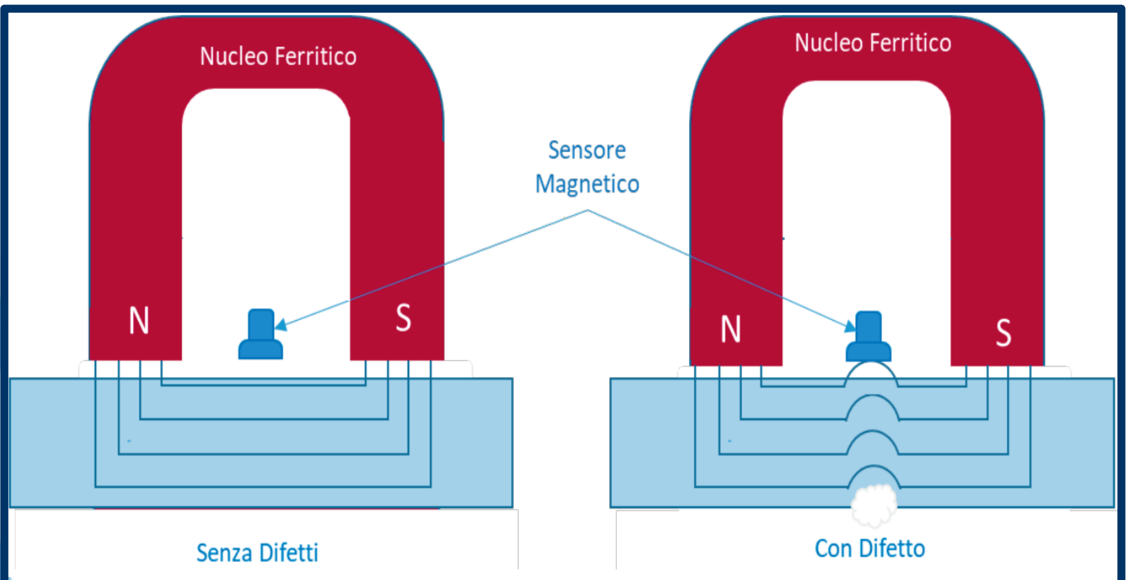
Damage inspection of ASTs

A simple visual inspection is not sufficient to quantify the damage of local corrosion in the tank's bottom plates. Special equipment and techniques are required to measure the actual corrosion depth. To control corrosion, the thickness of the bottom of ASTs are usually measured every 10 years or more, as part of a comprehensive inspection of the tank based on widespread standards (EEMUA, 2014; API, 2016a).

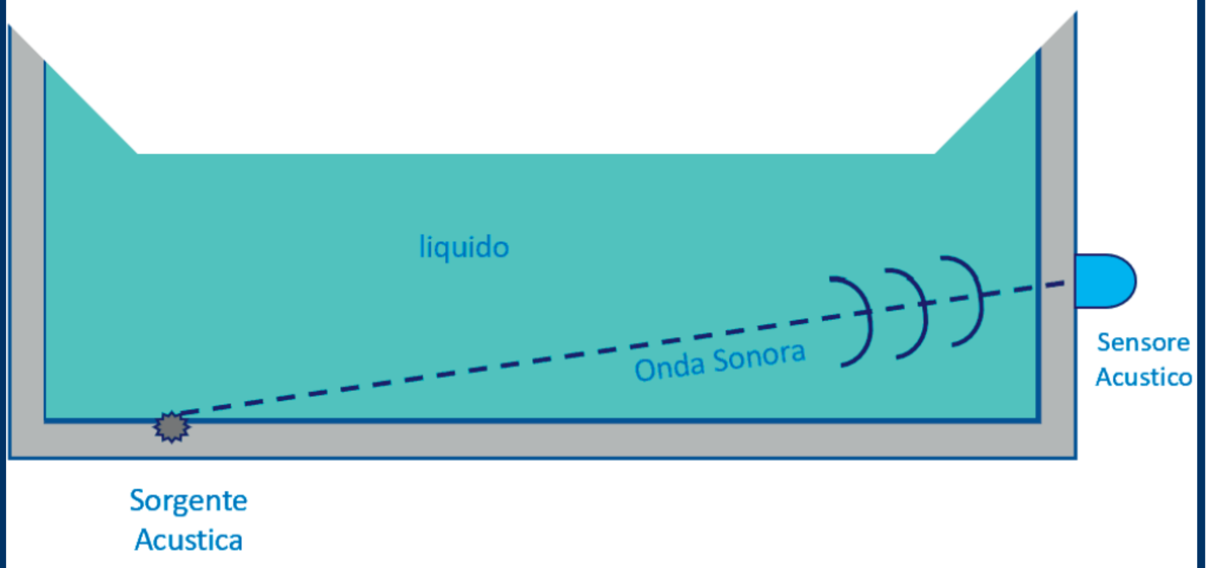
Accurate bottom integrity measurements can only be made during scheduled stops, when the tank is put out-of-service, emptied, carefully reclaimed and visually inspected.



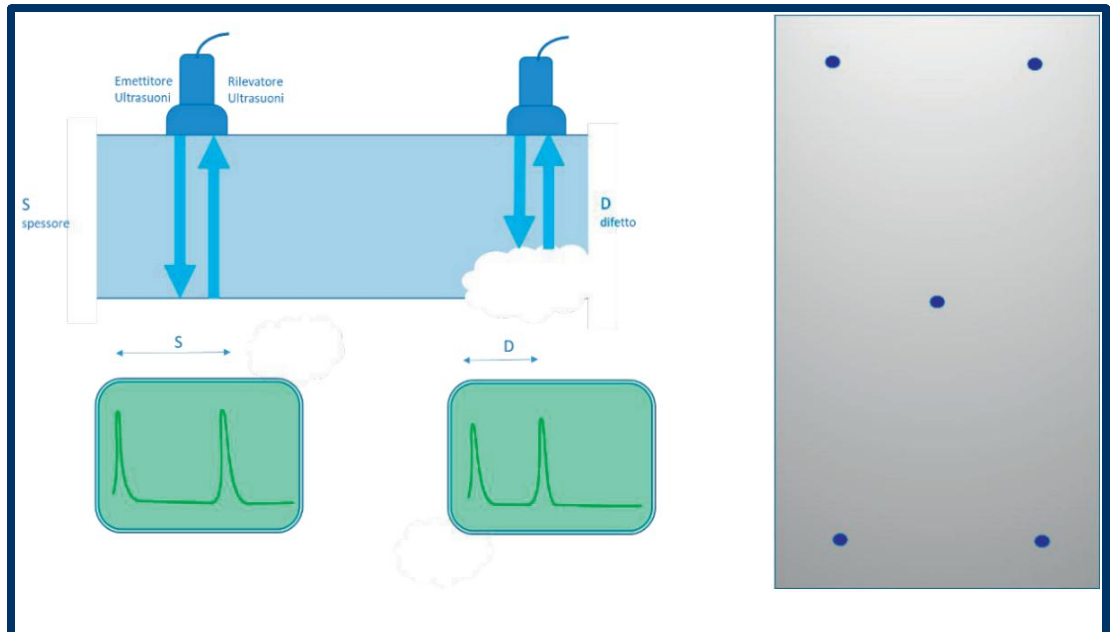
Most common measuring techniques



Magnetic Flux Leakage



Acoustic Emissions



Ultrasonic Thickness Measurements

Maria Francesca Milazzo, G. A. (2022). A probabilistic approach for the estimation of the residual useful lifetime of atmospheric storage tanks in oil industry.

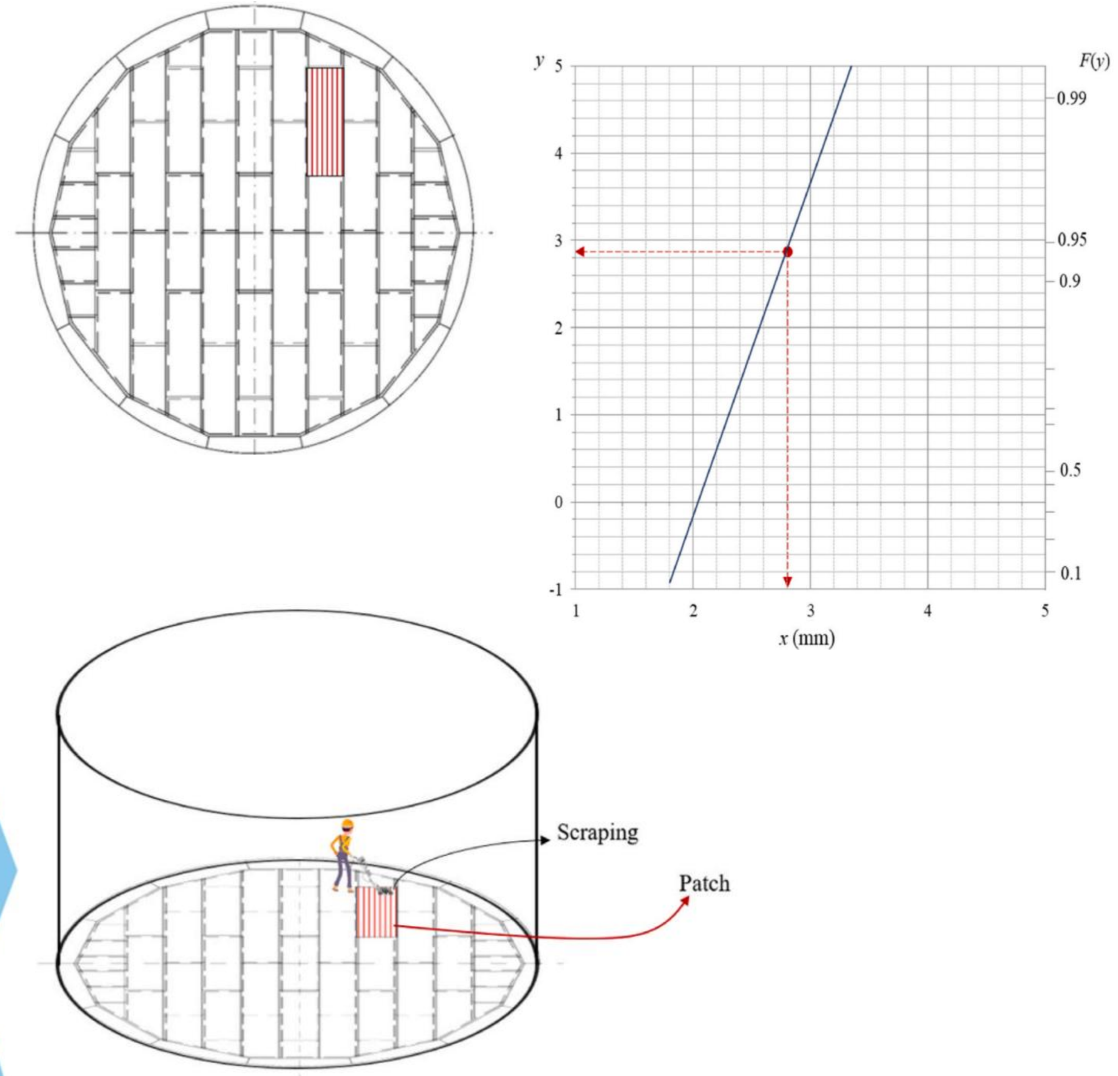
Objective

The goal of this work is to elaborate a solid procedure for the management of the safety of storage tanks, focusing on understanding corrosion in terms of pits number and their depth growth. An optimized managing procedure is useful for planning inspections at right time intervals.

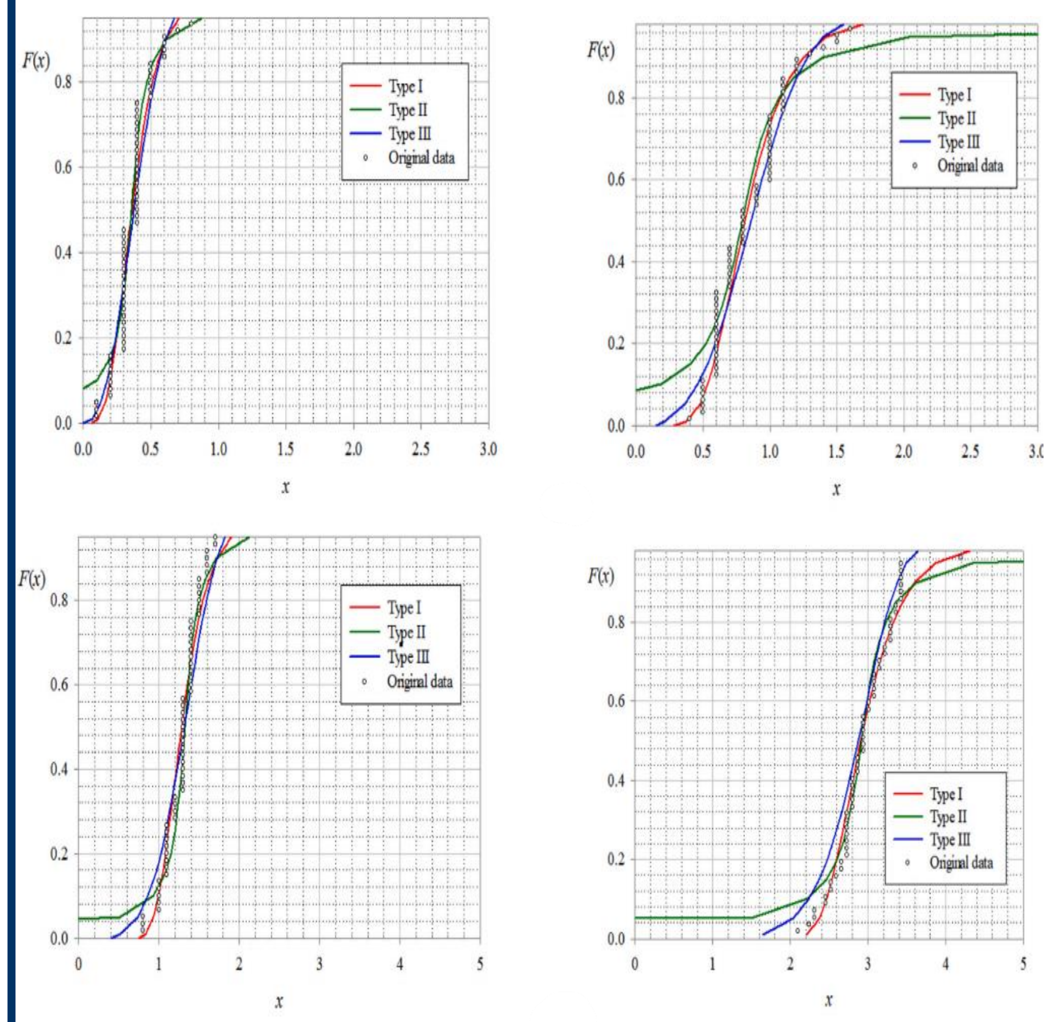
Given the complexity of the corrosion development, for this work a probabilistic approach is used to develop the prevision model.

Why a probabilistic approach?

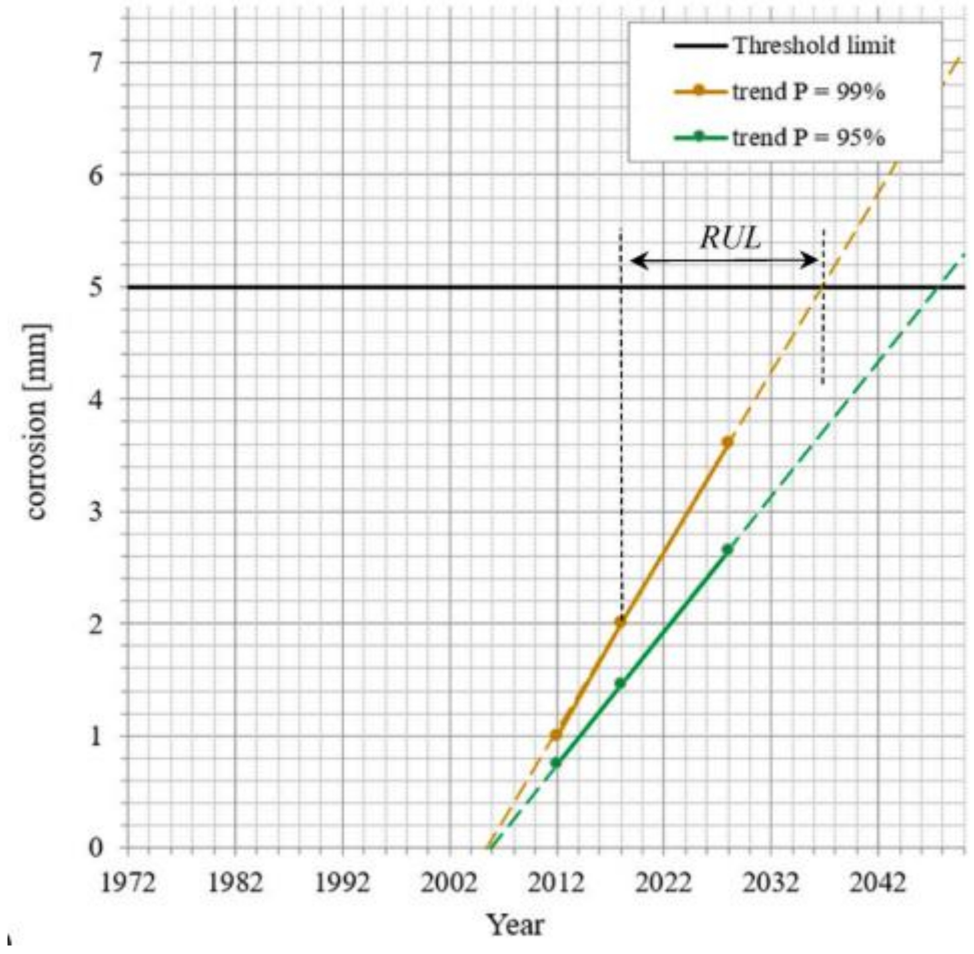
The scheduled stops and the special equipment required make inspections of ASTs quite costly. Furthermore, discrete thickness measurements cannot determine with certainty the maximum corrosion depth. Hence the probabilistic approach, using a stochastic model to characterize the phenomenon to better assess the risk of leakage.



Data collection



Data Modeling



Adjusted previsions

Maria Francesca Milazzo, G. A. (2022). A probabilistic approach for the estimation of the residual useful lifetime of atmospheric storage tanks in oil industry.

Experimental work – Setup

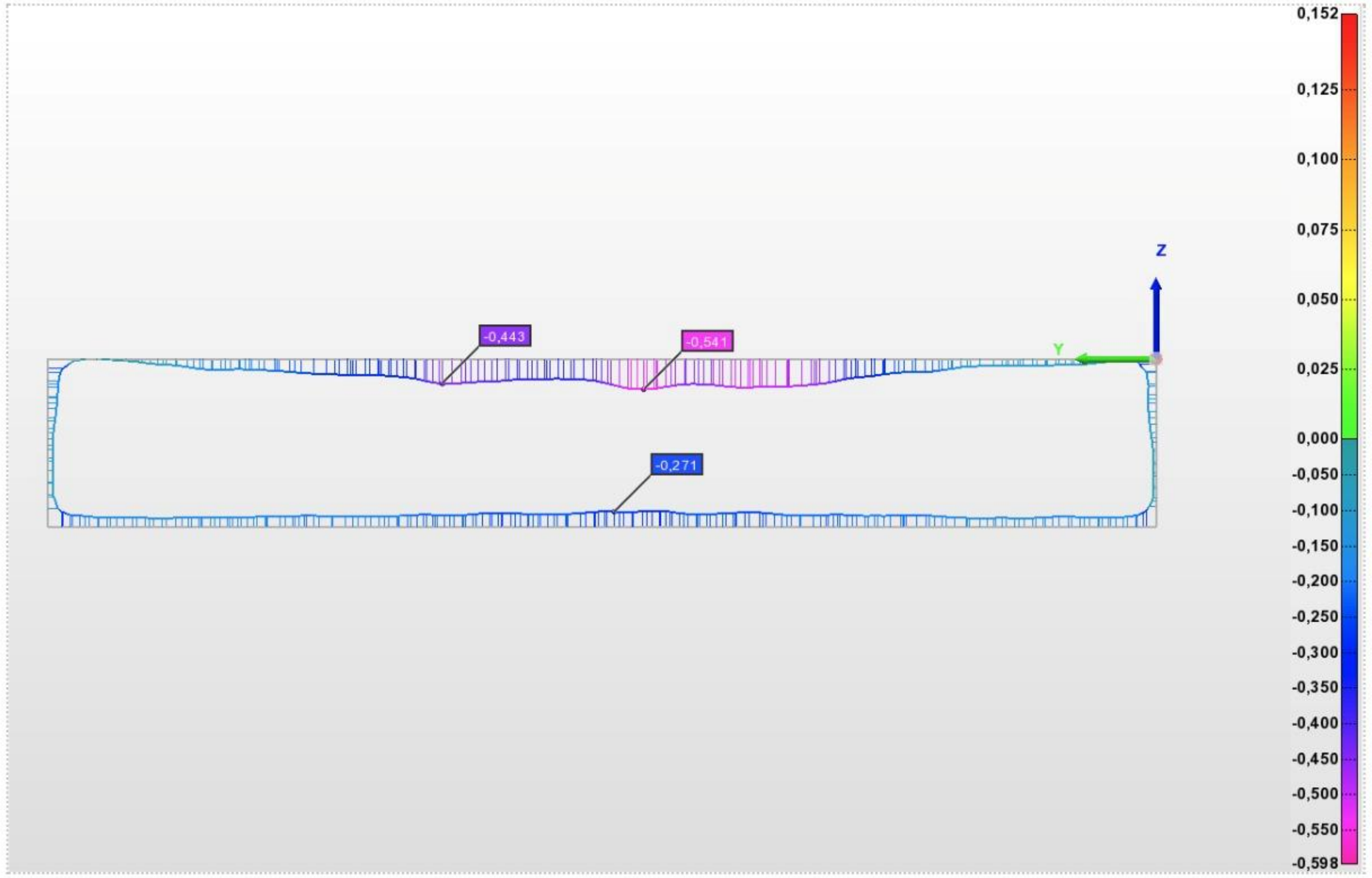
The study was carried out with various testing of steel samples, representative of the storage tank bottom, which were submerged in a commercial gasoil mixed with some additive solutions with a 4/1 ratio (Table 1).

Table 1: Characteristics of the additive solution (NACE TM0177)

Solution ID	Additive	pH
B	NaCl, glacial acetic acid and $Na_2S_2O_3$	2.5

To monitor the trend of the pitting corrosion on the samples, their depth was measured across the entire surface over one year with a laser scan.

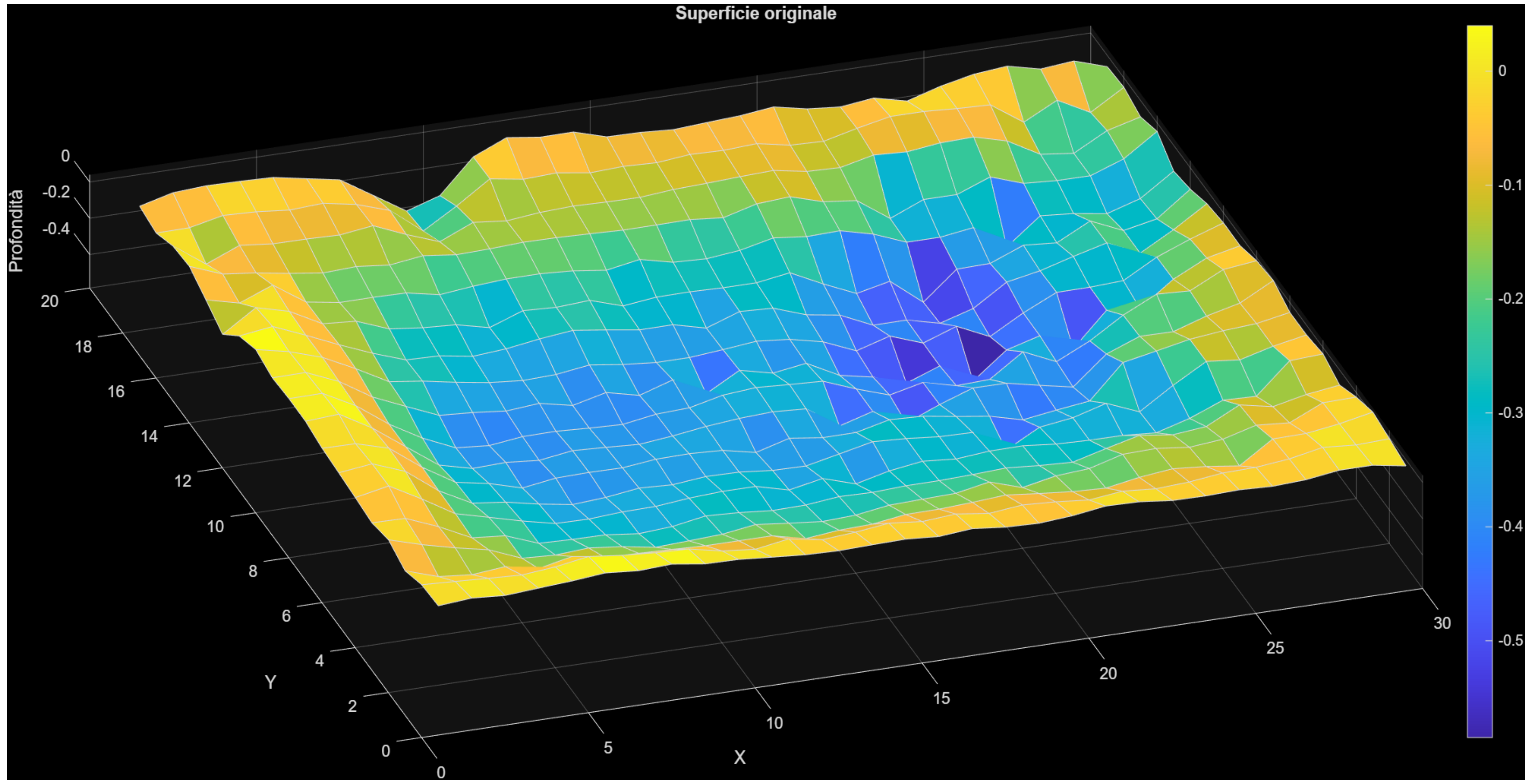
Steel samples setup



Maria Francesca Milazzo, G. A. (2022). A probabilistic approach for the estimation of the residual useful lifetime of atmospheric storage tanks in oil industry.
Milazzo M.F., Piperopoulos E., Khaskhoussi A., Scionti G., Bragatto P., Proverbio E., 2022, Influence of Operational Conditions on the Bottom Corrosion of Atmospheric Storage Tanks and Predicting Model Identification

Experimental work – Data Collection

Each sample was divided into several parts and for each of them the maximum corrosion depth was calculated. This simulates a wider range of data, without the needs of an extensive amount of samples.



Surface map of the sample

The code that process the data also remove the clear “border-effect” seen on the surface map.

N SubSamples

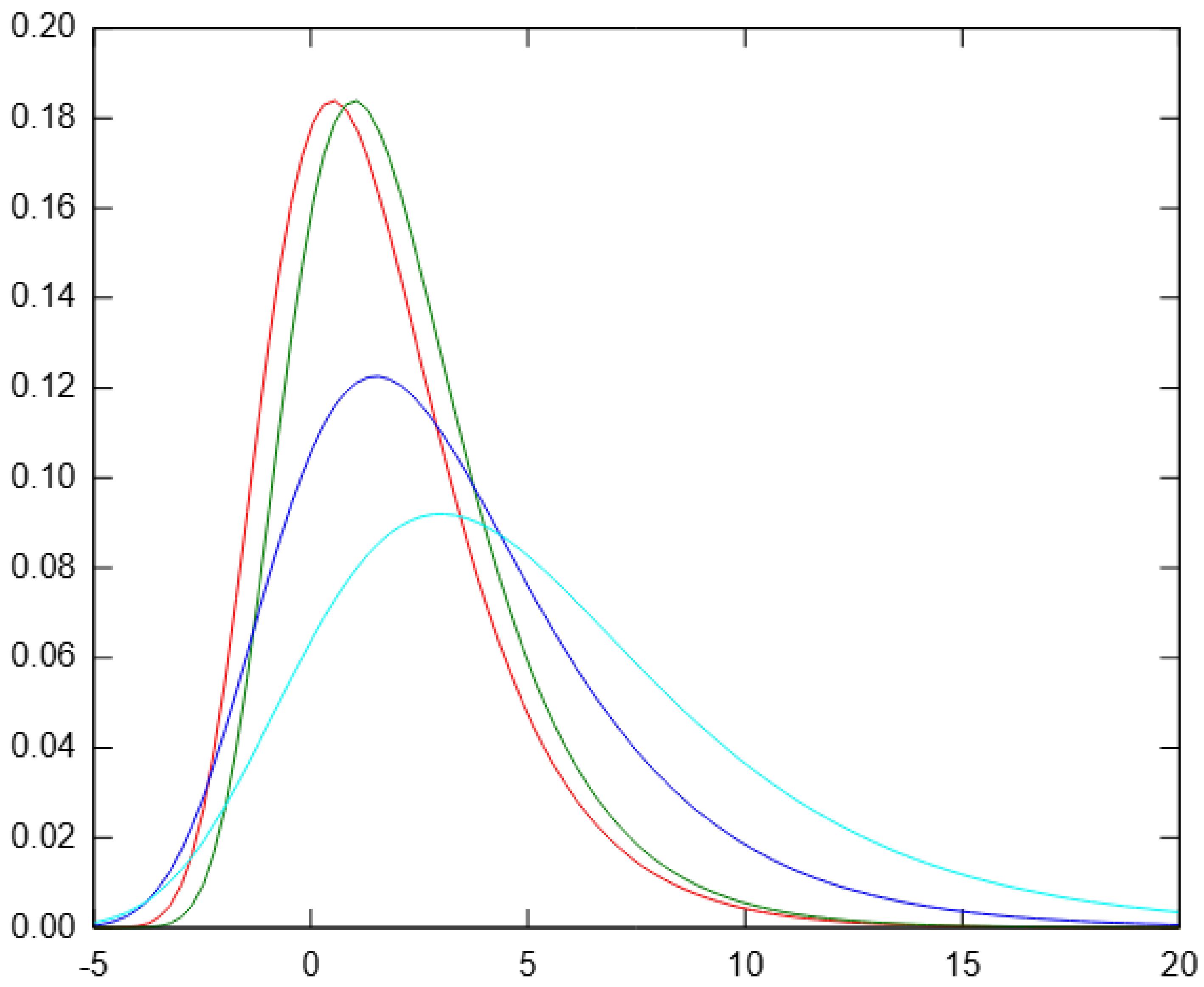
1	2	3	4	5	6	7	8	9	10
11	12	13	14	15	16	17	18	19	20
21	22	23	24	25	26	27	28	29	30
31	32	33	34	35	36	37	38	39	40
41	42	43	44	45	46	47	48	49	50
51	52	53	54	55	56	57	58	59	60
61	62	63	64	65	66	67	68	69	70

Experimental work – Data Distribution

With the maximum corrosion depth calculated for each subsample, the data is then fitted to a type 1 Gumbel distribution:

$$F_1(x) = exp\left[-exp\left(-\frac{x-\beta}{\alpha}\right)\right]$$

Where: $\begin{cases} x = corrosion\ depth \\ F(x) = cumulative\ probability \\ \alpha, \beta = distribution\ parameters \end{cases}$



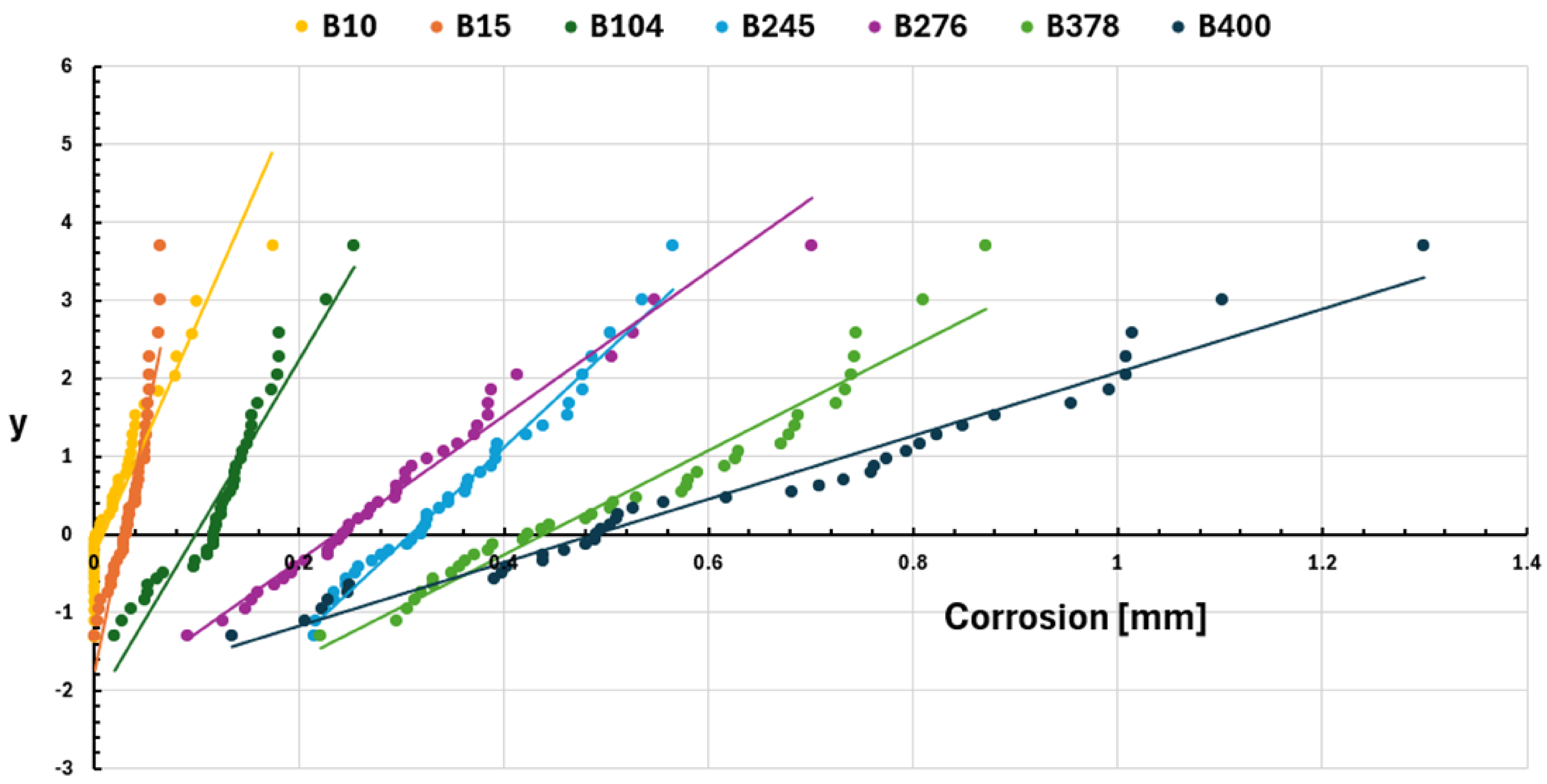
Then the distribution can be linearized with the introduction of the variable: $y = \frac{x-\beta}{\alpha}$

$$y = -ln\left[ln\left(\frac{1}{F(y)}\right)\right]$$

Experimental work – Data Distribution

By plotting y as a function of x in a semi-logaritmic diagram, the straight line obtained (called plot position) has a slope and intercept as functions of the distribution parameters, respectively ${}^{1}/_{\alpha}$ and $-\left({}^{\beta}/_{\alpha}\right)$.

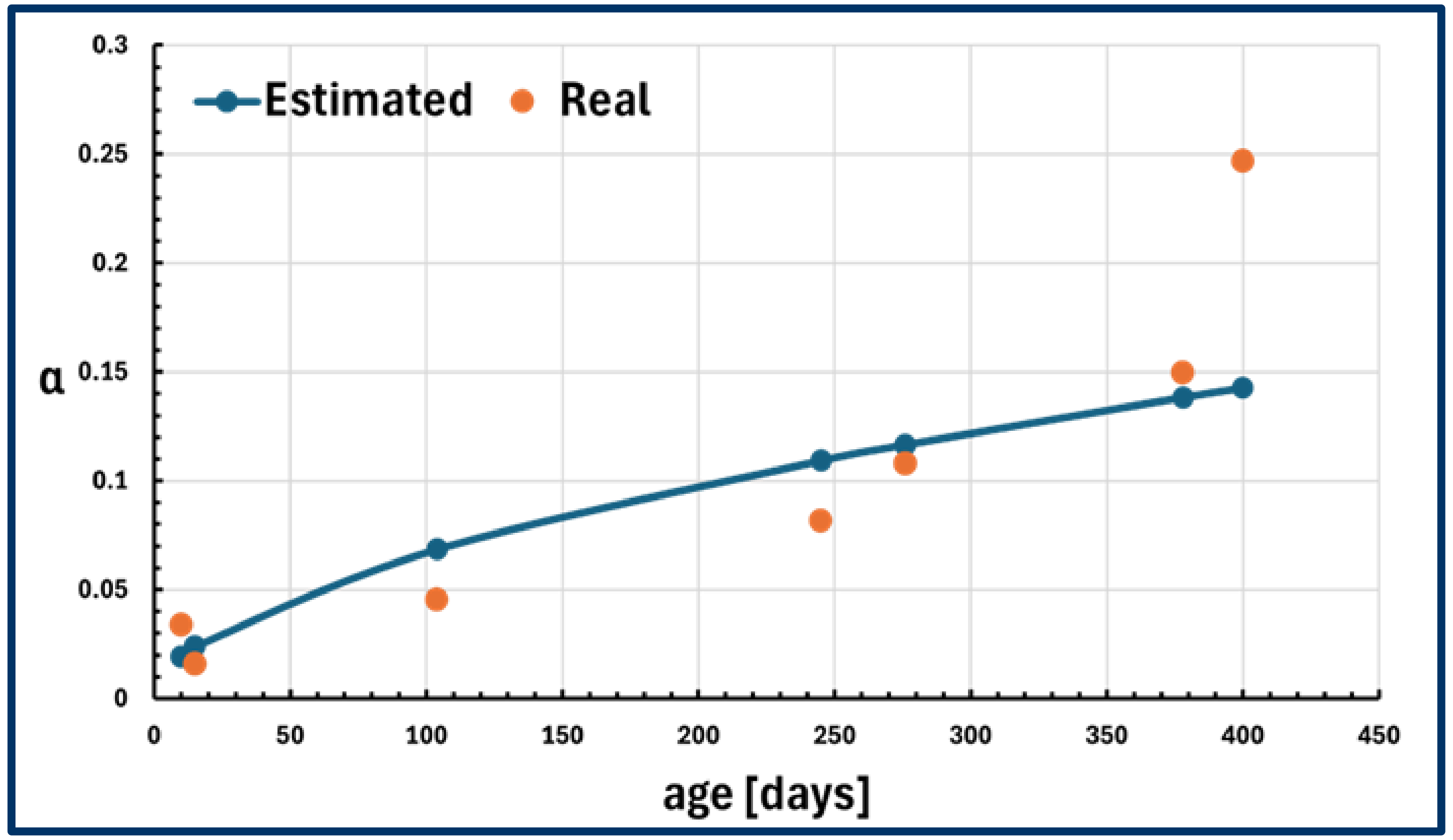
The cumulative probability is calculated as following: $F(y) = \frac{i}{n+1}$ where: $\begin{cases} i = rank\ of\ the\ measure \\ n = total\ number\ of\ measures \end{cases}$



The colors represent different samples that were exposed to the corrosive solution for different amount of time. The dots show the maximum corrosion measured for each subsample

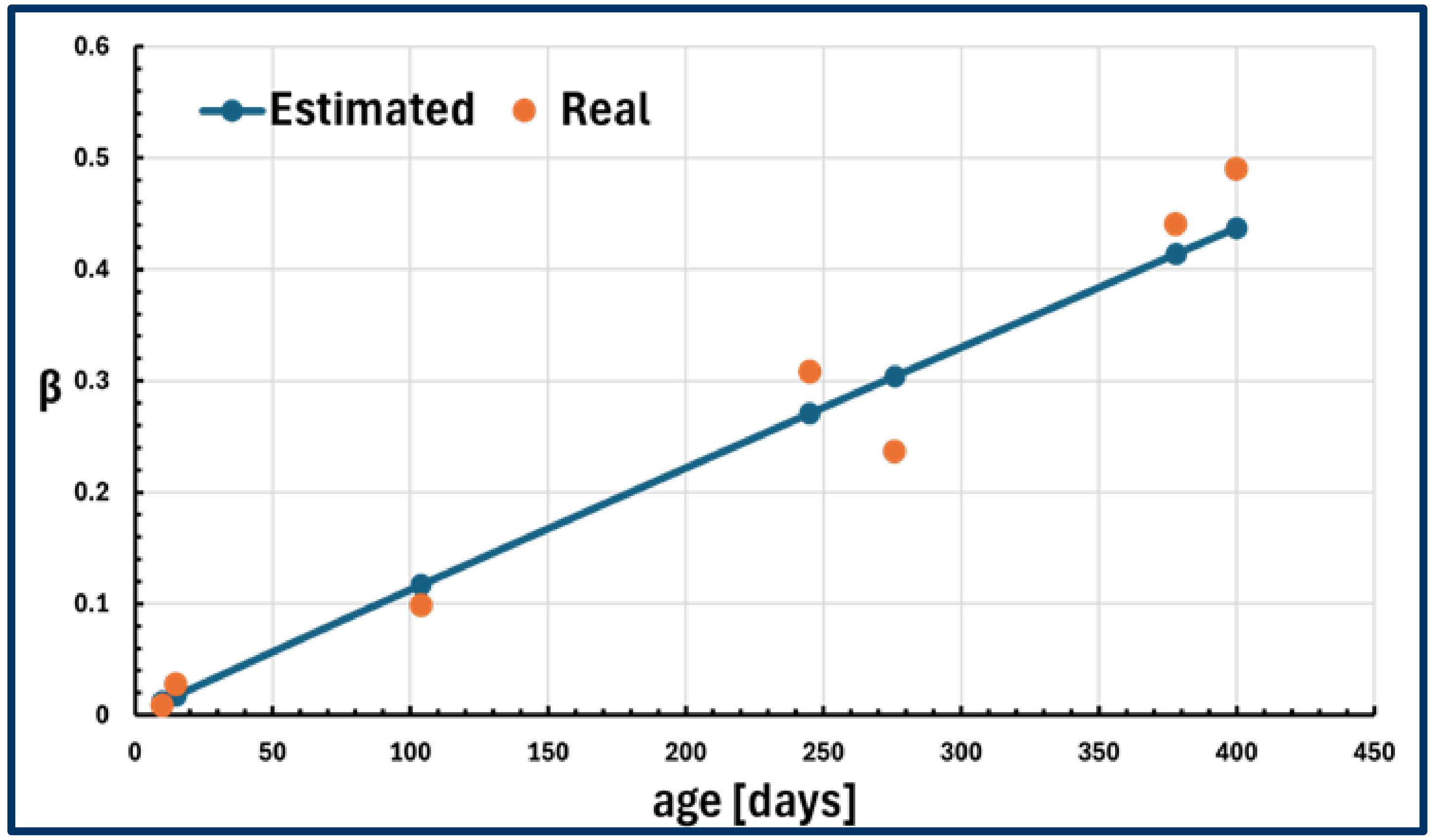
Experimental work – Modelling the corrosion development

With α and β parameters calculated, it is possible to capture their time dependance with a simple regression:



$$\alpha = a \cdot (age^{b})$$

$$\beta = a \cdot (age^{b})$$



The new parameters, a and b are calculated for each set of data, obtaining a distribution at each time frame

Experimental work – Modeling the Corrosion development

The previous previsions for α and β can be refined further with the Bayesian Inference, using the maximum corrosion depth measured as a parameter to adjust the estimated value. This is achieved following the process described below:

$\lambda'(\beta)$ A priori Distribution

$y = \frac{x_{max} - \beta}{\alpha}$ Reduced variable for the plot position

$y' = \frac{(x_{max}+dx) - \beta}{\alpha}$ Sensitivity of the reduced variable

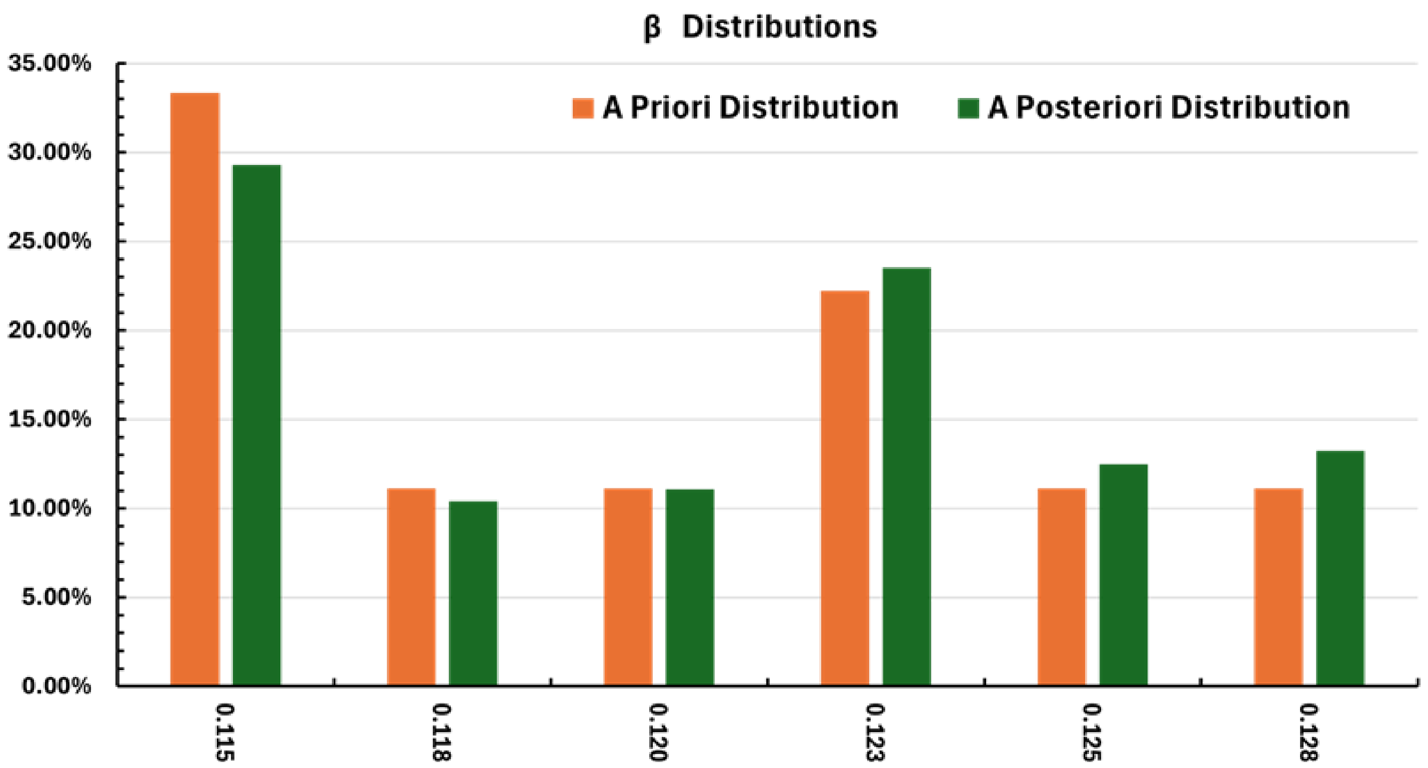
$f(x_{max}|\beta)$ Likelihood function

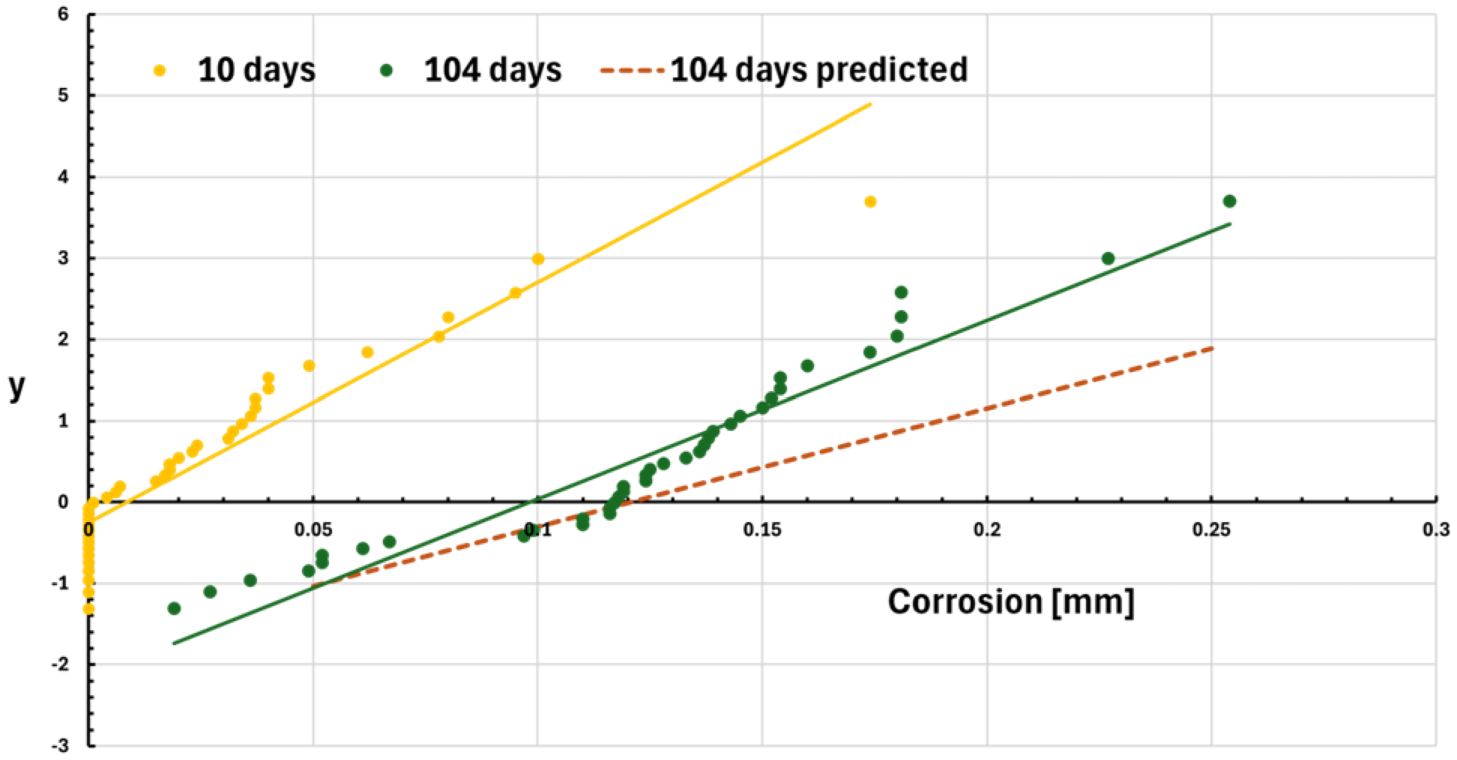
$\int \lambda'(\beta) \cdot f(x_{max}|\beta)$ → $\lambda''(\beta)$

A posteriori Distribution

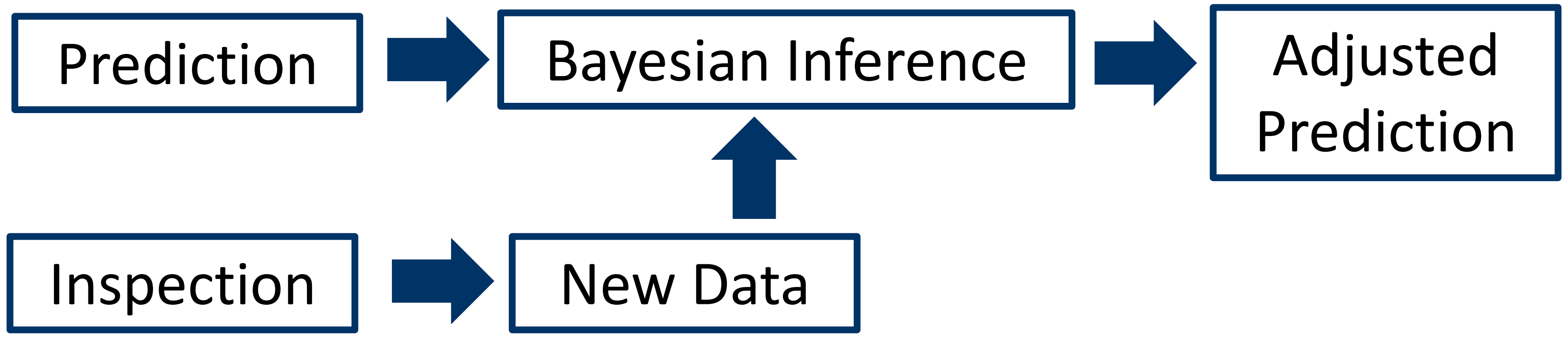
Experimental work – Preliminary results

The model was used to predict the corrosion development at 104 days and then compared to the real data. First, the beta distribution is derived only with the parameters a and b then, the distribution is adjusted using Bayesian Inference.





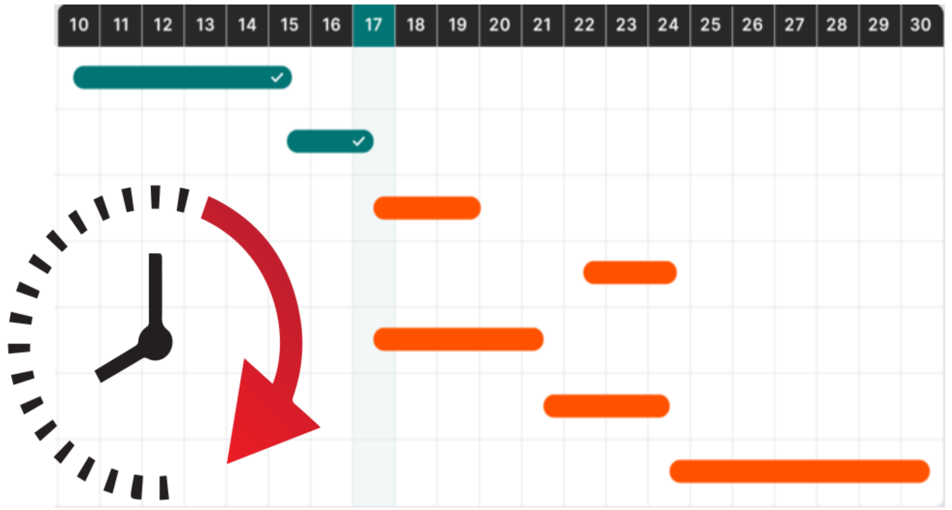
The results show how the Bayesian inference shift the beta distribution to the right, suggesting a more conservative prevision based on the maximum corrosion measurement.



Conclusions

In conclusion, the model, when combined with experimental work, provides a <u>non-invasive</u> methodology for estimating corrosion development. This innovation not only streamlines the planning of inspection activities but also contributes to a significant reduction in operational costs and minimizes risk exposure for technical personnel.

More “spaced-out” inspections



Less need of special monitoring techniques

Optimized Managing cost

Thank you for the attention