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A probabilistic approach for the estimation of the residual useful lifetime of atmospheric storage tanks in oil industry

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ABSTRACT

Based on the prediction of the equipment residual useful life, important decisions are made in oil industry to ensure a safe and profitable management. Atmospheric storage tanks are particularly critical from the safety point of view as their bottom is affected by localised corrosion (pitting), which is not easy to be monitored. The prediction of the useful lifetime defines the time up to which the equipment can continue to be in-service before the formation of holes where the greatest thinning is observed. In this study, the thickness data collected in subsequent inspections of the bottom of twenty-three large storage tanks of petroleum products has been processed by adopting an improved probabilistic approach. The method is unconventional and combines the consolidated extreme value theory and Bayes' formula to quantify the probability of thinning below a fixed limit and, thus, predict the remaining useful lifetime, as well as the optimal time for the next full inspection. Data collected allowed the validation of the forecast model.

1. Introduction

Atmospheric storage tanks (ASTs) are essential for the containment of hazardous substances in major accident hazard establishments. Since they are expected to operate over long periods, ASTs are particularly critical from the safety point of view if appropriate integrity monitoring and management plans are not adopted. In refineries, oil terminals, depots, and petrochemical plants, a serious problem is the corrosion of the bottom of ASTs containing hydrocarbons, especially for tanks that have been in service for more than 40 years. The phenomenon could cause the release of substances with adverse consequences for humans and the environment due to both their flammability and eco-toxicity (Argyropoulos et al., 2012; Laurent et al., 2021; Ikwan et al., 2021). Major releases of hydrocarbons fall under both the European Seveso III Directive for the prevention of major accidents (Directive, 2012/18/EU – EU Council, 2012), whilst minor leakages, prolonged over time, are under the Industrial Emission Directive for the integrated prevention and control of pollution (Directive, 2010/75/EU – EU Council, 2010). The release of flammable vapours is, furthermore, ruled by the European Directive for the protection of workers potentially at risk from explosive atmosphere (Directive, 1999/92/EC – EU Council, 1999).

To control corrosion, the thicknesses of the bottom of ASTs are usually measured every 10 years or more, as part of a comprehensive inspection of the entire tank based on widespread standards (EEMUA, 2014; API, 2016a). Accurate bottom integrity measurements can only be made during the scheduled stops, when the tank is put out-of-service, emptied, carefully reclaimed, and visually inspected. Currently, the use of the *Magnetic Flux Leakage* (MFL) technique is the best available technique (EU Council, 2006), but the *Ultrasonic Thickness Measurements* (UTM) are still common and necessary for the thickness detection in difficult points. *Acoustic Emissions* (AE) could be useful to verify the presence of ongoing degradation for in-service tanks, however, they are absolutely complementary to direct thickness measurements. In addition to the criticalities discussed above, there are also problems related to the occupational safety as inspections involve the worker enters into the tank and has to remain for a long time in a highly dangerous environment while executing the measurements. Currently, the corrosion monitoring of in-service tanks is not easy, although some researchers investigated the potential of the AE technique for the estimation of the corrosion rate at the bottom and annular plates of ASTs (Park et al., 2006; Sakamoto et al., 2013). In Europe AE is classified as the "Best Available Technology" for monitoring the conditions of the bottom of an in-service AST (EU Council, 2006), whereas Guided Waves (GW) are a further promising technique to control corrosion for in-service tanks (Cobb 2018). Some operators have experimented bottom testing for in-service tanks by using specialised robots, which have shown a great potential to perform these tasks remotely and efficiently (Tu et al., 2016; Anvo et al., 2018; Acar, and YaŞar, 2019; Slaughter 2019). Robots integrate technologies for visual analysis, ultrasonic scanning, other sensors, and functionalities that make easier to obtain accurate data.

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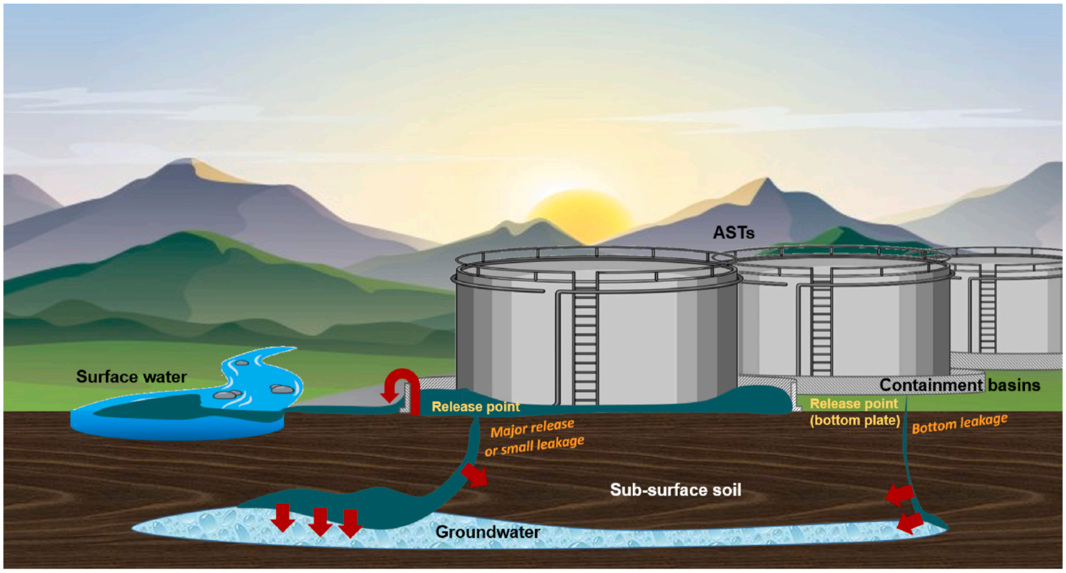

Fig. 1. Catastrophic scenario of release from the bottom of a floating roof AST and migration pathways for the released substance.

These solutions allow the operator gaining access in confined spaces, under the harshest conditions, cleaning surfaces and carrying out inspections (internal, external and even underwater), therefore it is possible to perform tasks that are complex and imperative for the safety and maintenance of facilities. Nevertheless, available prototypes need further improvements to make them reliable in practical operations.

Due to the well-known ageing issue (Wood et al., 2013; Semmler, 2016; Gyenes and Wood, 2016; OECD, 2017), the Seveso Directive explicitly requires the operators of major hazard accident establishments to demonstrate the adoption of proper management plans to control deterioration processes, including the bottom corrosion of ASTs. There are established methods and tools to accomplish this task (EEMUA, 2014; API, 2016a), but their application sometimes could be burdensome. Other methods have been recently developed to verify the adequacy of ageing management plans, these are based on index methods (Milazzo and Bragatto, 2019; Yacine et al., 2020). In this context, it is also useful for the operators to be able to make predictions, to calculate the probability of release due to ageing and to know how long to safely extend the residual useful lifetime (*RUL*). The knowledge of the probability of leakage from the bottom and annular plate of ASTs allows integrating accidental scenarios caused by ageing into the safety report of major accident hazard establishments, but it is also needed to know the potential for the environmental contamination of the site. The knowledge of the actual residual lifetime and the interval before the subsequent inspection is essential to prevent releases and monitor the integrity of tanks.

Based on popular standards (EEMUA, 2014; API, 2016a), the corrosion rate is estimated as the ratio between the thickness reduction and the time interval between two inspections. It is used to estimate the *RUL* and plan appropriate maintenance. Unfortunately, discrete thickness measurements cannot determine with certainty the maximum corrosion depth of the bottom of storage tanks, where materials are usually characterised by localised corrosion in the form of pits. For this reason, to assess the probability of leakage from the bottom, it would be useful to use a probabilistic approach with a stochastic modelling of the phenomenon. The use of the extreme value theory is frequent (HSE, 2002; Bolzoni et al., 2006; Velázquez et al., 2009; Shibata, 2011) and several authors used the Gumbel distribution to describe the pitting corrosion (Shibata, 1991; Valor et al., 2007; Melchers and Ahammed, 2018); others researches questioned about the use of this distribution (Melchers, 2005; Asadi and Melchers, 2017) and even proposed different alternatives (Jarrah et al., 2011; Valor et al., 2013). The literature shows some applications of the extreme value theory to the bottom of tanks, e.g. Joshi (1994) analysed corrosion data obtained by UTM of plates of aboveground storage tanks containing crude oil; Shibata (1991) determined the optimal return period and predicted the maximum corrosion from a Gumbel diagram; Kasai et al. (2016) combined the analysis of extreme values and Bayesian inference to predict the maximum corrosion depth.

Taking advantage of the available research on this topic and by referring to the bottom of ASTs containing hydrocarbons, this work aims at the use of the consolidated models for the statistical analysis of the pitting corrosion to achieve the following objectives:

- to quantify the probability of the critical pit (i.e. the probability of reaching the threshold thickness according to common standards) and the probability of leakage to be used in the quantitative risk assessment;
- to make predictions of the probability of the critical pit after a given time;
- to make appropriate decisions for a safe extension of the in-service time, based on probabilistic predictions of the *RUL* obtained from inspection data of the AST.

This article is structured as follows. After a short overview about safety issues and the basic concepts, Section 2 describes the methodology adopted to achieve the above objectives. It is based on the use of the extreme value theory and the Bayesian inference to derive probabilistic predictions about the condition of the tank over the time by exploiting the knowledge acquired from the latest inspections and those for tanks of similar contexts. Section 3 presents applicative examples, including data sampling procedures, and two case-studies. Section 4 reports the data analysis made for 23 ASTs and a discussion about the main findings of the study. Finally, Section 5 gives the conclusions of the work.

2. Methodology

2.1. Overview

Internal corrosion in ASTs (product side) can be caused by (i) the presence of aggressive substances or contaminants in the stored product, and (ii) the entry and accumulation of water in the tank due to its presence in the product, the condensation from the tank ventilation, and the infiltration of rainwater from the roof seals (Myers, 1997).

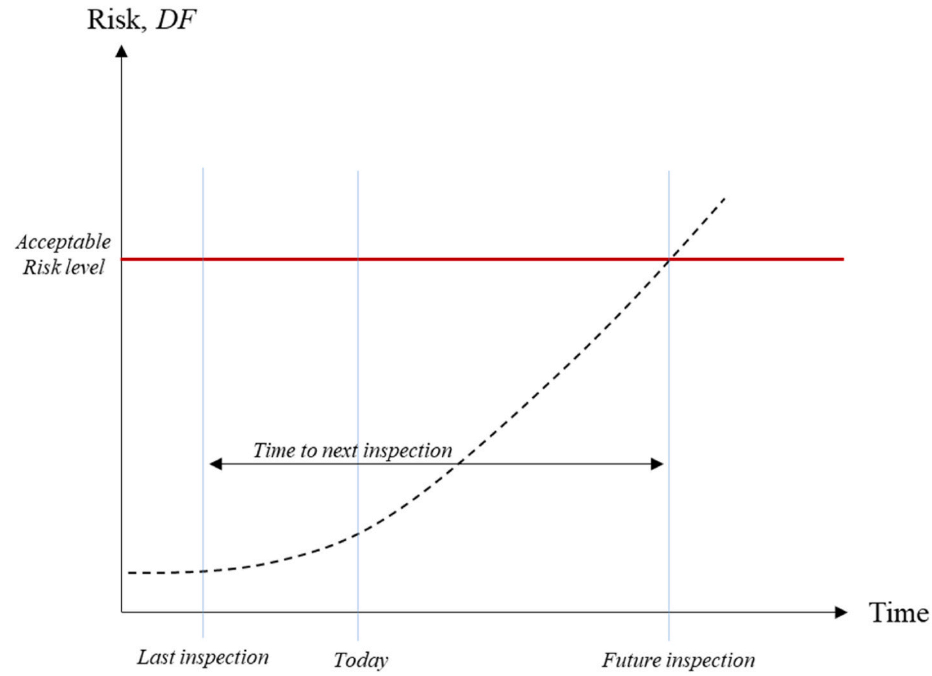

Fig. 2. Identification of the time to next inspection.

Generalised corrosion of the bottom plates usually occurs where water collects; the most critical area is the one adjacent to the shell for bottoms sloping towards the outside (cone-up) and the central one when the slope is inwards (cone-down). *Localised corrosion* may occur in stagnation areas, such as support feet of the drain or the heating coil, plates under the roof support struts, etc. Another form of corrosion is pitting, usually caused by acid salts, hydrogen sulphide, water, bacteria (microorganisms), etc. (Caines et al., 2013; Bhandari et al., 2015; Kannan et al., 2020). Corrosion phenomena could also affect the welds of the sheets of the bottom.

Typical release scenarios to be investigated for ASTs containing hydrocarbons (Myers, 1997; Topalis, 2017) include: the floor leakage and the floor catastrophic rupture, the shell leakage and the shell catastrophic rupture, and the roof vapour leakage. The modelling of the consequences depends on the amount of the released substance. In case of scenarios associated with the bottom of the tank, the following events should be accounted for: (i) minor losses from holes in the bottom plates, (ii) releases inside the containment basin (small and medium leakages) (iii) overflow of the substance collected in the containment basin (catastrophic release). In the first case, if the loss is not detected in advance, the liquid could pass through any cracks in the concrete basis and contaminate the soil and the groundwater. The second case could result in a pool fire in case of ignition, but the flammable vapours, trapped between the basin and the tank, could cause even a flash fire or an explosion; in case of defects in the bottom of the containment basin, soil and groundwater contamination is also possible. The worst case is associated to a catastrophic release and results in a contamination of the surface water, sub-surface soil and the groundwater. Fig. 1 shows the migration pathways for the substance in case of catastrophic release.

The Risk-Based Inspection (RBI) approach is widespread for risk assessment in the oil & gas, refining, petrochemical and chemical industries (API, 2016a; API, 2016b). The risk is calculated as the combination of the probability of failure (*PoF*) and the consequence of failure (*CoF*). The *PoF* is the product of the generic failure frequency (*GFF*) for a given type of tank, the management factor (*MF*) and the damage factor (*DF*). Fig. 2 illustrates the process to determine next inspection date. The user sets a maximum acceptable risk level, and then the risk is calculated as a function of the time; if it exceeds the maximum acceptable level, an inspection is suggested. Next inspection date is obtained as the intersection of the risk curve and the maximum acceptable risk line.

The API recommended practices require a large amount of information to be able to exploit the knowledge about damage mechanisms and is generally applied through the support of proper software. These standards are suitable for large establishments, but for small ones, including fuel depots, they require many resources and can be too costly. In addition, results are based on the knowledge of the damage mechanisms which, although respectable, can never be specific for the context under study. The approach proposed in this work for the quantification of the probability of the critical pit and the residual lifetime is condition-based, therefore it is less conservative than the standard approaches. The methodology is based on the use of the well-known extreme value theory. To make predictions about the equipment condition, aimed at the estimation of the residual lifetime, this theory has been combined with the Bayesian inference.

2.2. Basic concepts

Pioneering studies about the statistical nature of corrosion and its relationships with inspections are due to several researchers (Gumbel, 1954; Hawn, 1977). Amongst various works, Joshi (1994) used the extreme value theory to extrapolate statistical information about pitting corrosion from small inspection patches to a whole AST. The concept the author applied is based on the evidence that a statistical sample which obviously contains less than an entire population of data may follow the distribution of the whole dataset. This means that, when an entire population of pits is available by a detailed surface scan, covering the entire tank, the statistical analysis of data produces the same distribution pattern of a limited sample. This is extremely important given that a complete dataset rarely is available. The use of these methods for the analysis of corrosion data of the bottom of ASTs is widespread in Japan since the 1980's, while it is not common in other countries (HSE, 2002).

Localised corrosion is a stochastic process that can assume different forms whose statistics could be different. The choice of the probability distribution is crucial for the following use as well as for the accuracy of the distribution parameters; the confidence limits depend on the number of data points. By referring to the set of maximum corrosion depths of the bottom of an AST (x), as the number of the measures (n) in the set grows, the statistical behaviour of the variable becomes insensitive, and

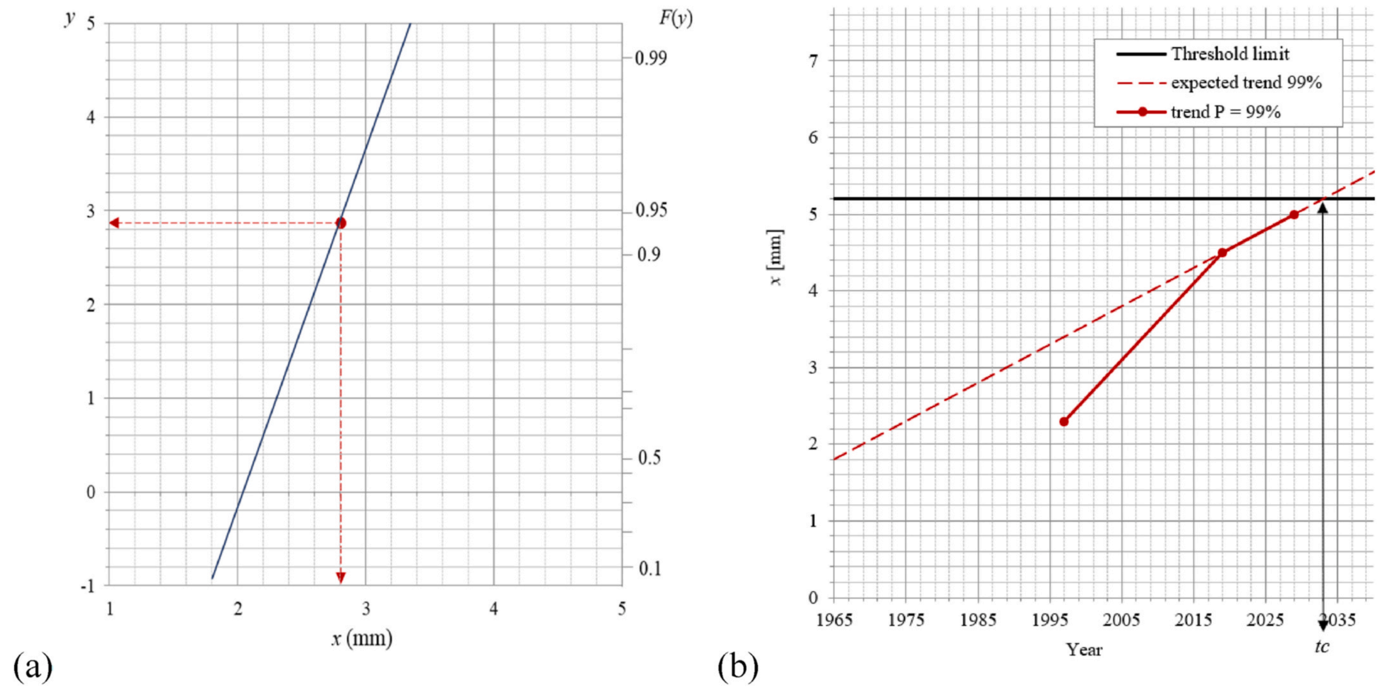

Fig. 3. (a) Probability of bottom perforation; (b) Residual Useful Lifetime.

Table 1
Characteristics of the ASTs used in this investigation.

ID Tank	Substance	No. plates	Commissioning year
TK01	Diesel fuel	203	1965
TK02	Gasoline	59	1965
TK03	Gasoline	122	1972
TK04	Crude oil	84	2012
TK05	Fuel oil	16	1954
TK06	Diesel fuel	64	1972
TK07	Diesel fuel	305	1975
TK08	Diesel fuel	39	2000
TK09	Gasoline	51	2000
TK10	Gasoline	65	1997
TK11	Diesel fuel	91	1997
TK12	Diesel fuel	82	2006
TK13	Diesel fuel	83	1984
TK14	Diesel fuel	80	1965
TK15	Diesel fuel	79	1965
TK16	Gasoline	76	1965
TK17	Gasoline	89	1965
TK18	Naphtha solvent	59	1962
TK19	Diesel fuel	209	1972
TK20	Gasoline	209	1973
TK21	Diesel fuel	231	1990
TK22	Diesel fuel	88	1974
TK23	Diesel fuel	120	1965

the distribution of the extreme values tends to some limit forms (Gumbel, 1954; Berretta, 2009). These limit distributions are classified into 3 types according to the shape of their tails:

$$F_I(x) = \exp\left[-\exp\left(\frac{x-\beta}{\alpha}\right)\right] \quad \text{distribution type I} \tag{1}$$

$$F_{II}(x) = \begin{cases} 0 & x < \beta \\ \exp\left(-\left(\frac{x-\beta}{\alpha}\right)\right)^{-k} & x \geq \beta \end{cases} \quad \text{distribution type II} \tag{2}$$

$$F_{III}(x) \begin{cases} \exp\left(-\left(\frac{x-\beta}{\alpha}\right)\right)^{k} & x \leq \beta \\ 0 & x > \beta \end{cases} \quad \text{distribution type III} \tag{3}$$

where: α, β and k are parameters of the distribution.

The *type I distribution* (so-called Gumbel distribution) is applied when the field of the parent distribution is unlimited at the top and the right tail of the density distribution exponentially decays (Gumbel, 1954). It is represented by Equation (1) as n approaches $+\infty$. The *type II distribution* is given by Equation (2) and is valid when the parent distribution is defined in the range $0 < x < +\infty$. Finally, the *type III distribution* assumes the form of Equation (3) and is used when the parent distribution has an upper limit.

Alternatively, a *generalised extreme-value* distribution (GEV) can be also used (Jenkinson, 1955):

$$F_{GEV}(x) = \exp\left\{-\left[1 + \frac{\gamma(x-\beta)}{\alpha}\right]^{1/\gamma}\right\} \qquad \gamma \cdot x \leq \alpha + \beta \cdot \gamma \tag{4}$$

where: α = scale parameter; β = location parameter; γ = shape parameter.

The shape parameter could be used to understand the best fitting with respect to the limit forms of the distribution given above. This can be done according to the following rules: *type I* if $\gamma = 0$, *type II* if $\gamma > 0$, and *type III* if $\gamma < 0$. To this scope, three additional criteria can be used (VOSE, 2017; Akaike, 1974; Hannan and Quin, 1979; Schwartz, 1997):

$$SIC = \ln(n) \cdot j - 2 \cdot \ln(L_{\max}) \quad \text{information criterion I (Schwarz, 1997)} \tag{5}$$

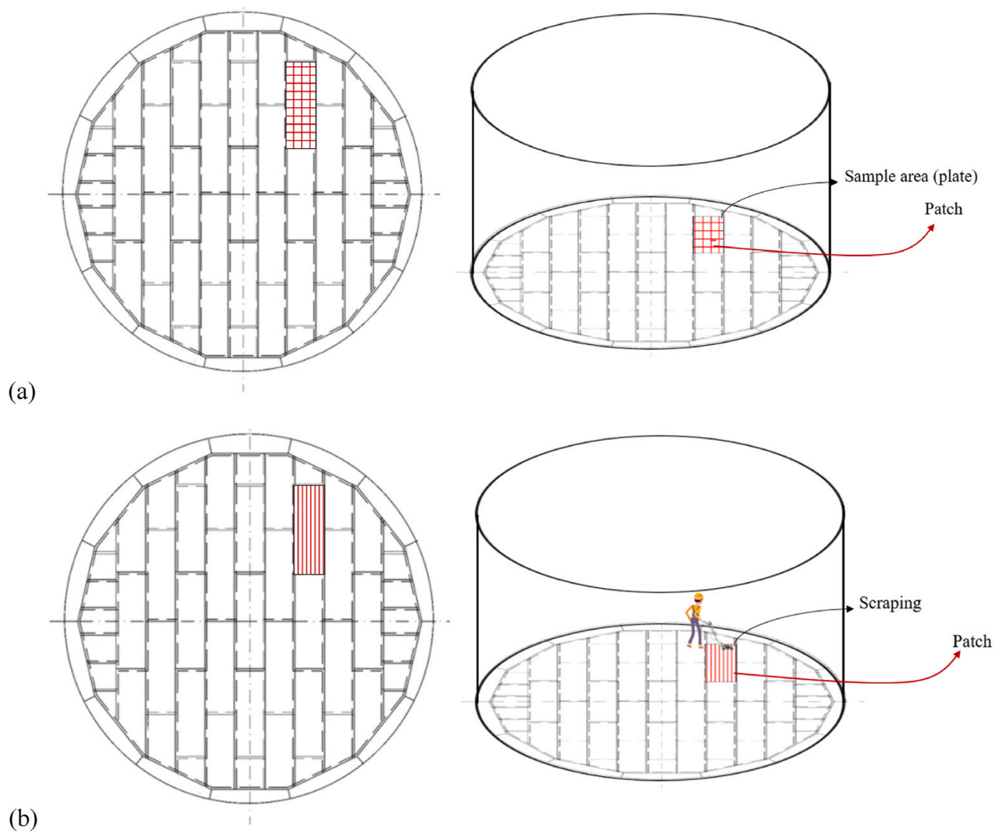

Fig. 4. Data collection from the bottom of a tank to produce extreme values: (a) by ultrasonic technique, and (b) by magnetic flux leakage technique.

$$AIC = \left(\frac{2 \cdot n}{n - j - 1}\right) \cdot j - 2 \cdot \ln(L_{\max}) \text{ information criterion II (Akaike, 1974)} \quad (6)$$

$$HQIC = 2 \cdot \ln[\ln(n)] \cdot j - 2 \cdot \ln(L_{\max}) \text{ information criterion III (Hannan and Quinn, 1979)} \quad (7)$$

where: n = total number of measures; j = number of parameters to be estimated; 2 ln ($L_{\max}$) = estimate of the deviance from the model fit.

The rule to use of these criteria is that the lower an information criterion, the better the fit. After the choice of the distribution type and its transformation to the *type I*, in case the best fitting is given by a *type II* or *III* distribution, the plot position can be constructed by introducing a reduced variate (y), which allows the linearization of the equation of the extreme value distribution:

$$F(x) = \exp\left(-\exp\left(-\frac{x - \beta}{\alpha}\right)\right) \quad (8)$$

$$y = \frac{x - \beta}{\alpha} \quad (9)$$

$$y = -\ln\left[\ln\left({}^{1}/_{F(y)}\right)\right] \quad (10)$$

where: $F(x)$ = cumulative probability function (Gumbel distribution).

By plotting y as a function of x, a straight line (*plot position* or *Gumbel diagram*) is obtained, whose slope and intercept respectively are $1/\alpha$ and – (β/α). The cumulative probability is simply calculated by means of the following equation:

$$F(y) = \frac{i}{n + 1} \quad (11)$$

where: i = rank of the measure; n = total number of measures.

Table 2
Characteristics of the investigated atmospheric storage tanks.

Information	Tank A	Tank B
Type	Fixed roof tank	External floating roof tank
Substance	Diesel fuel	Gasoline
Diameter	30 m	22 m
Material bottom plates	Carbon steel	Carbon steel
Number bottom plates	64	59
Bottom area	707 m^2	380 m^2
Nominal thickness	7.5 mm	7.7 mm
Year of commissioning	1972	1965
Year of inspection 1	2002	1997
Technique for inspection 1	Visual inspection Ultrasonic Thickness Measure	Visual inspection Ultrasonic Thickness Measure
Year of inspection 2	2018	2019
Technique for inspection 2	Visual inspection Ultrasonic Thickness Measure	Magnetic Flux Leakage

Table 3
Basic statistics for bottom inspections.

Tank	ID inspection	Year	Inspection technique	Average thickness	Standard deviation	Maximum corrosion depth
A	1	2002	UTM	7.11 mm	0.164	0.8 mm
	2	2018	UTM	6.63 mm	0.303	1.8 mm
B	1	1997	UTM	6.38 mm	0.270	2.5 mm
	2	2019	MFL	4.73 mm	0.419	4.34 mm

Table 4
Scale and location parameters (first inspection).

ID Tank	Substance	Distribution parameter		Inspection time (year)
		α	β	
TK01	Diesel fuel	0.152	1.194	25
TK02	Gasoline	0.243	1.185	32
TK03	Gasoline	0.276	0.229	14
TK04	Crude oil	0.038	0.089	7
TK05	Fuel oil	0.496	1.005	51
TK06	Diesel fuel	0.143	0.307	30
TK07	Diesel fuel	0.187	0.839	44
TK08	Diesel fuel	0.061	0.203	16
TK09	Gasoline	0.081	0.320	19
TK10	Gasoline	0.062	0.160	44
TK11	Diesel fuel	0.321	0.521	22
TK12	Diesel fuel	0.076	0.204	13
TK13	Diesel fuel	0.258	0.428	33
TK14	Diesel fuel	0.128	0.639	54
TK15	Diesel fuel	0.334	0.714	51
TK16	Gasoline	0.282	0.359	44
TK17	Gasoline	0.118	0.528	52
TK18	Naphtha solvent	0.261	2.041	48
TK19	Diesel fuel	0.127	0.824	25
TK20	Gasoline	0.189	0.182	42
TK21	Diesel fuel	0.215	0.718	23
TK22	Diesel fuel	0.246	2.282	30
TK23	Diesel fuel	0.298	1.123	46

2.3. Probability of the critical pit and predictions

The plot position can be used to read the probability of a pit having a depth lower than a given value. As shown in Fig. 3a, a corrosion depth less or equal to 2.8 mm occurs with a probability of 0.94 ($y = 2.9$), hence a corrosion depth higher than 2.8 mm has a probability of 0.06. The probability of tank perforation, i.e. the probability of the pit, having a depth equal to the thickness of the tank bottom, can be directly read on the plot position or calculated by using the distribution parameters.

The knowledge of the distribution of the scale and position parameters (which defines the pit depth probability distribution) over the time (a priori probability distributions) can be exploited to make a forecast of both parameters by means of the Bayesian inference. The Bayesian inference allows determining the posterior probability distribution of α and β after a certain time:

$$\chi''(\alpha|x_{\max}) = \frac{\chi'(\alpha)\cdot f(x_{\max}|\alpha)}{\int \chi'(\alpha)\cdot f(x_{\max}|\alpha)\cdot d\alpha} \tag{12}$$

$$\lambda''(\beta|x_{\max}) = \frac{\lambda'(\beta)\cdot f(x_{\max}|\beta)}{\int \lambda'(\beta)\cdot f(x_{\max}|\beta)\cdot d\beta} \tag{13}$$

where: $\chi'(\alpha)$, $\lambda'(\beta)$ = a priori probability distributions of α and β; $\chi''(\alpha|x_{\max})$, $\lambda''(\beta|x_{\max})$ = a posteriori probability distribution of α and β after a certain time; $f(x_{\max}|\alpha)$, $f(x_{\max}|\beta)$ = likelihood functions; $x_{\max}$ = maximum corrosion value detected during the last inspection.

The prediction of the value of α and β at a given time is obtained by summing the products between the values of the parameter and related posterior probabilities.

2.4. Residual useful lifetime

The prediction of the parameters α and β at a given time allows elaborating a new plot position, which makes possible to determine the corrosion rate and the *RUL*. Once the probability of a corrosion depth (x) is higher than a given value is read on the current plot position, the corrosion associated with the same probability after a given period is obtained from the new plot position.

For each probability, the corrosion depth can be plotted vs. time as shown in Fig. 3b. The trend is linear if it is extrapolated from two points, i.e. the current and predicted corrosion depths associated with the same probability. In case several previous inspections are available, the tendence is not linear and can be represented by a curve that is the best fitting for the points associated with the past, current e predicted corrosion depths. The angular coefficient of the line/curve gives the corrosion rate, which will be constant in the case of a linear trend and variable for a no-linear one. By extrapolating the plot x vs. time (for a given probability), it is possible to determine t_c that is the time when the critical thickness is reached with a probability P. The *RUL* is obtained by subtracting the current year from t_c.

3. Applicative examples

3.1. Data collection

As part of an agreement between INAIL and the association *unem* (Unione Energie per la Mobilità that is the Italian association of oil and associated industries), several inspections of the bottom of ASTs have been collected in 2020, these refers to the 23 tanks listed Table 1. The AST diameter ranges between 10 and 40 m and currently the average age is 42 years, even though most data was gathered a few years earlier. Some inspections have been performed by using the Ultrasound Technique (UTM) and others by means of the Magnetic Flux Leakage one (MFL). The investigation included the analysis of 2504 bottom plates. At least five measurements for each plate have been provided in the case of UTM, whilst MFL measurements could be basically considered continuous and with a resolution of a few centimetres. Information about previous inspections and nominal thicknesses was available for most tanks.

Two categories of liquid hydrocarbons were contained inside the ASTs, namely gasoline and diesel fuel. According to their typology, ASTs have been grouped into fixed and floating roof tanks, it must be pointed that internal floating roof tanks are unusual in Italy. Within each group, only those whose characteristics allow them being considered similar from the point of view of the corrosion mechanisms have been included. The main characteristics, accounted for during the selection, were the combination of stored product and bottom material, the size and construction characteristics and the internal and external conditions.

For the purposes of this study, the following classification has been possible:

- group 1: fixed roof tank containing diesel fuel,
- group 2: external floating roof tank containing gasoline.

To show the application of the methodology illustrated in Section 2 for the determination of the probability of perforation of the tank (current and predicted values) and the calculation of the residual useful

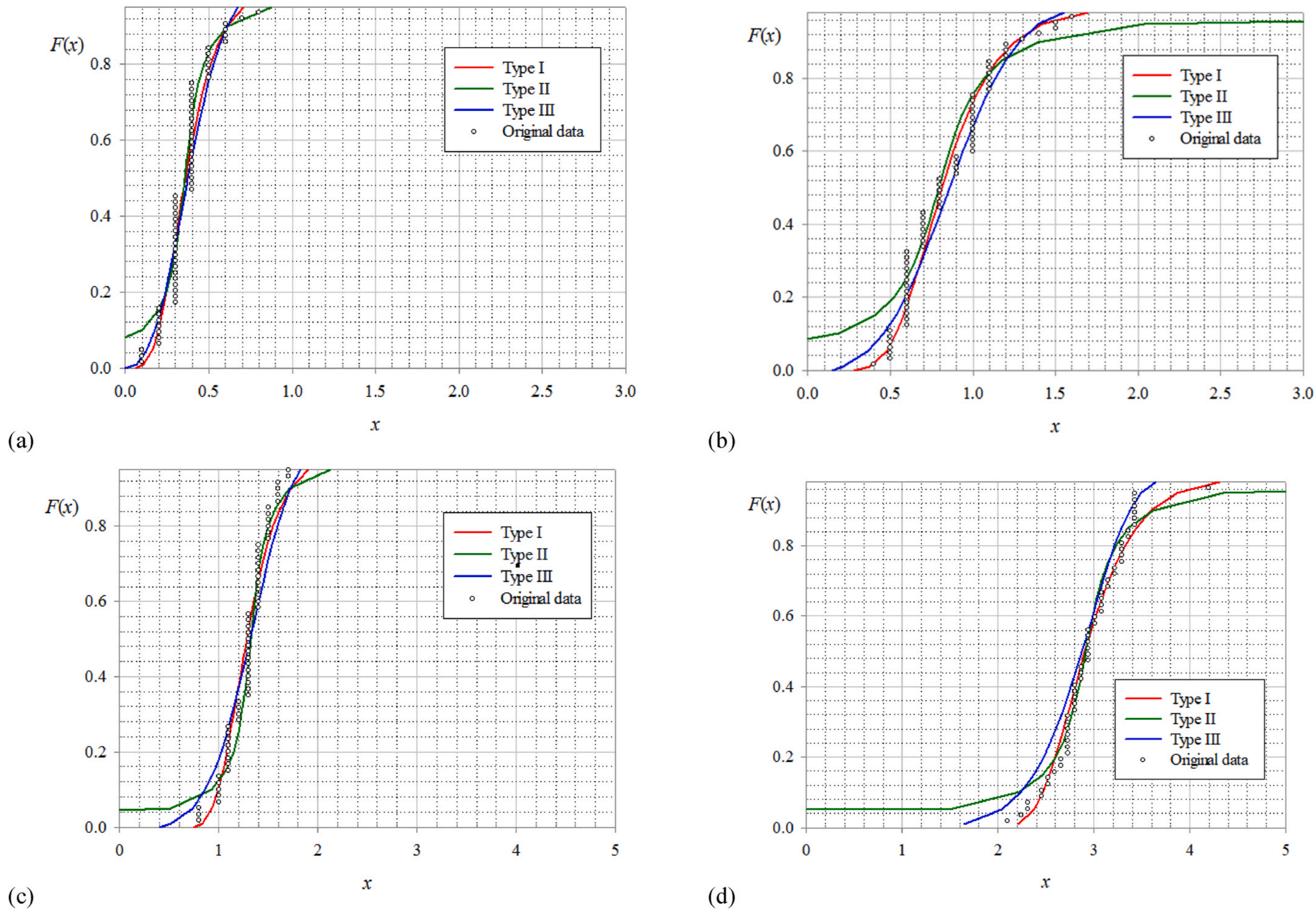

Fig. 5. Cumulative distribution curves for the inspection of (a) Tank A in 1990; (b) Tank A in 2019; (c) Tank B in 1997; (d) Tank B in 2019.

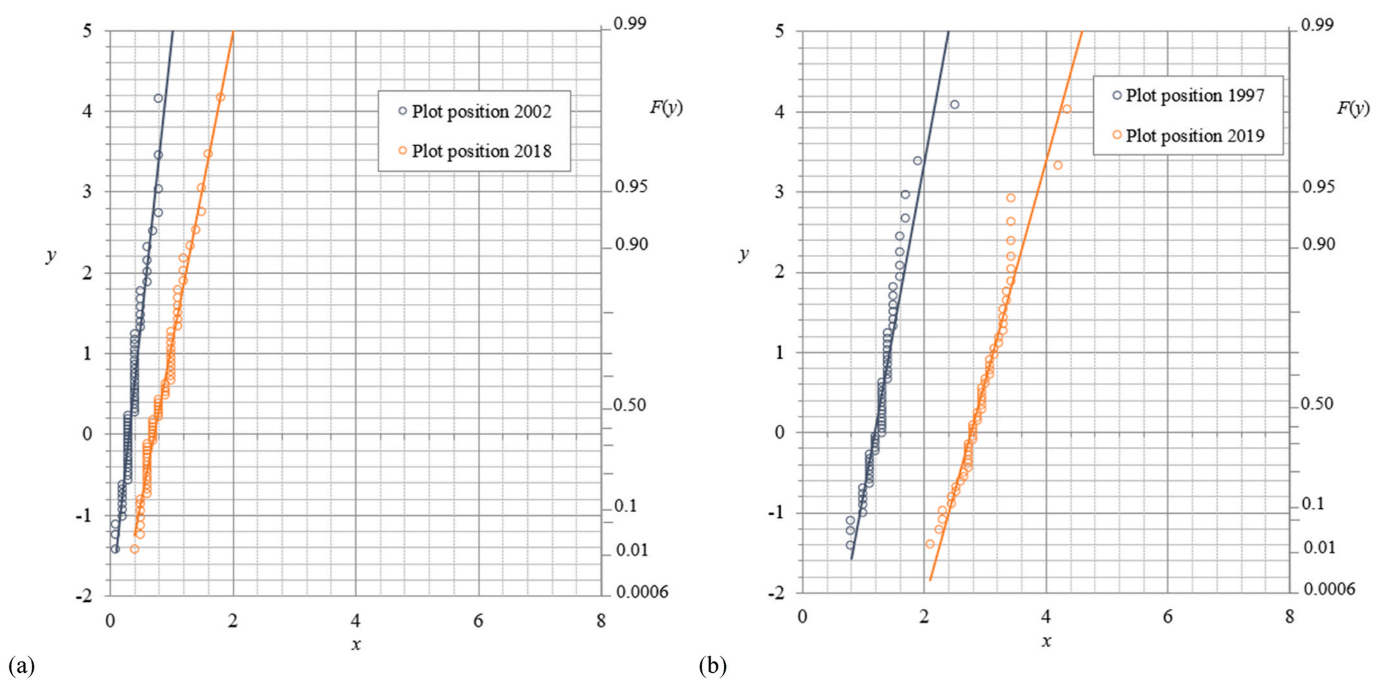

Fig. 6. Plot positions: (a) Tank A and (b) Tank B.

Table 5
Parameters of the distributions and probability of the critical pit.

Tank A		
Parameter	Inspection 2002	Inspection 2018
scale parameter α	0.143	0.258
location parameters β	0.307	0.723
probability critical pit ($x > 5$ mm)	$5.11{\cdot}10^{-15}$	$6.32{\cdot}10^{-8}$
Tank B		
Parameter	**Inspection 1997**	Inspection 2019
scale parameter α	0.242	0.364
location parameters β	1.181	2.768
probability critical pit ($x > 5.2$ mm)	$6.34{\cdot}10^{-8}$	0.001

lifetime, two cases have been selected, i.e. a fixed roof tank containing diesel fuel and a floating roof tank storing gasoline. The ASTs of Table 1 have been used to investigate the temporal trend of the distribution parameters in order to include the knowledge derived from inspections in similar contexts within the forecast model.

3.2. Data sampling

According to the guidelines of HSE (2002) for the use of statistics in the analysis of corrosion, each bottom of tank must firstly be divided into sample areas to be inspected (areas with similar corrosion properties) and within each area a few samples (so-called patches) must be identified.

Before 2011, the inspections made for the tanks of Table 1 have been made by ultrasonic thickness gauging from the topside, which also determined if there was underside corrosion at each measured location. Through this sampling technique, only a small percentage of the floor has been gauged, therefore, to reduce the possibility that significant corrosion could be undetected, a careful visual inspection has been always performed before and after these measurements. The visual inspection also allowed the distinction between topside and underside corrosion. When UTM measurements of the bottom are available, the sample areas are the plates, but a rigorous subdivision into patches is usually not carried out and the number of measures per plate is very small. However, it should be noted that the visual inspection allows identifying the areas where there are the highest levels of corrosion and therefore the points where the measurements should be carried out (Fig. 4a). These points represent the locations where the minimum value of thickness is detected for each hypothetical patch and, thus, the maximum corrosion depths. Generally, at least 5 random readings are performed per patch.

The most recent inspections (after 2011) have been performed by monitoring the changes in magnetic flux. The technique cannot be used to inspect welded areas or those immediately adjacent to the shell. The use of these techniques permits to inspect much larger percentages of the bottom by means of several scrapings per plate made by the movement of the device (Fig. 4b). The effective scanned area is ~100% and the loss of thickness is reported in a scale of 20%, 40%, 60% and 80% of material loss. All areas should be further investigated by visual inspection to assess whether the corrosive attack is topside of underside of the bottom plates.

3.3. Case-studies

The case studies are two large atmospheric storage tanks. Their characteristics are given in Table 2: Tank A is representative of group 1 and tank B of group 2. The basic statistics for the bottom inspections are summarised in Table 3.

The sets of the maximum corrosion depths were extracted from the data collected during each inspection. The corrosion depth is the difference between the nominal thickness of the plate and the measured thickness:

$$x = s_o - s \tag{14}$$

where: x = corrosion depth; s_o = nominal thickness of the plate; s = measured thickness.

4. Data analysis and discussion

For each inspection of the bottom of the ASTs of Table 1, the extremes value theory has been applied as indicated in Section 2.2. After

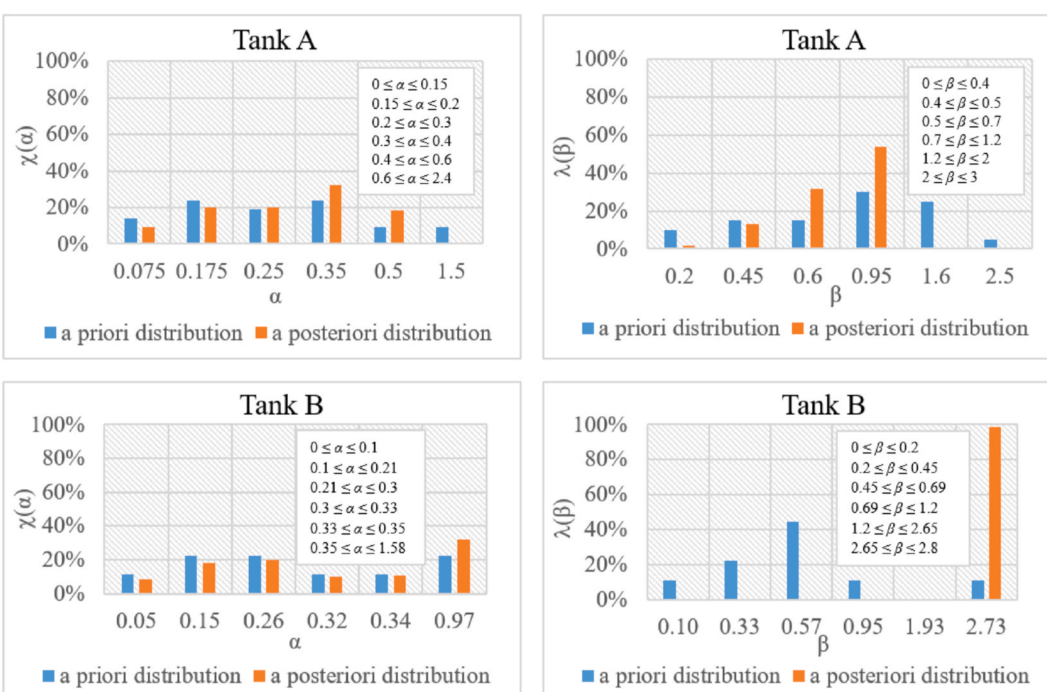

Fig. 7. A priori and posteriori distributions for the scale and location parameters used for the validation.

Table 6
Parameters of the distributions and probability of the critical pit.

Tank A		
Parameter	Forecast value (2018)	Actual value (2018)
scale parameter α	0.297	0.258
location parameters β	0.762	0.723
probability critical pit ($x > 5$ mm)	$6.35 \cdot 10^{-7}$	$6.32 \cdot 10^{-8}$
Tank B		
Parameter	**Forecast value (2019)**	**Actual value (2019)**
scale parameter α	0.463	0.364
location parameters β	2.693	2.768
probability critical pit ($x > 5.2$ mm)	0.004	0.001

the identification of the probability distribution that best fit the corrosion depths, the values of the scale and position parameters have been estimated (Table 4). By using past inspections, an approximate temporal dependence has been obtained for both parameters by interpolating the data as suggested by Shibata (1991) and choosing the best fitting curve. By overlapping all temporal trends of the scale and position parameters of the tanks that belong to the same group, it was possible to determine the distribution of the parameters at any given time (a priori probability distribution). These curves are given in the Supplementary materials (Figure S1 and S2).

4.1. Application of the extreme values theory and selection of the best fitting distribution

The sets of maximum corrosion depths, collected during the inspections 1 and 2 of the bottom of the tank A and B, have been analysed. The data fitting, made with the ModelRisk (VOSE, 2017), gave the cumulative distribution curves of Fig. 5 (the parameters of each distribution obtained with the ModelRisk are given in the Supplementary materials – Table S1). The data of both inspections of Tank A fits the *type I* distribution, even if there is a small overlap for higher x with *type II* in 2002; whereas the inspection data of Tank B overlaps the *type I* for both inspections, except a small overlap with *type III* in 1997 for higher x. The application of the information criteria confirms the *type I* as the best fitting distribution for Tank A and Tank B. The values of *SIC*, *AIC* and *HQIC* are shown in the Supplementary Materials (Table S1).

4.2. Probability of the critical pit and predictions

By using the most recent plot positions (defined as in Section 2.3), it was possible to determine the current probabilities of having a pit's depth less or equal to the critical value. The critical depth has been assumed to be the nominal thickness of the plate subtracted by 2.5 mm, which is the threshold value proposed by EEMUA (2014). It must be emphasised that this is a very conservative value, i.e. the precautionary depth. Unlike the shell of the tank, there is no structural damage risk for the bottom but only the risk of perforation.

The parameters of the distribution have been obtained through a linear regression of the plot y vs. x. These have been compared with those obtained from the ModelRisk. The probabilities of the pit having a depth less or equal to the critical value cannot be read from Fig. 6a and b, these have been numerically calculated by using the parameters of the distributions and Equation (9). Table 5 gives the values of α and β and the probability of the critical pit for each inspection of Tank A and Tank B. By comparing the evolution of the phenomenon over the time, the mode of the Gumbel distribution (β) became greater during the last in-service period, as well as the scale parameter (α). The change of α is due to the increase of the variances of the maximum depth caused by the evolution of the localised corrosion. The probabilities are absolutely negligible for both ASTs, expect for the second inspection of Tank B when the value 0.001 is reached, therefore interventions are required to make safe the bottom and prevent releases of dangerous substances.

The application of the EVT combined with Bayesian inference to the data collected during the inspection 2 of both tanks (as indicated in Section 2.3) has been used to predict the trend of corrosion maxima and the probability of the critical pit after 10 years. The forecast model has been firstly validated by comparing the predictions at the time of the second inspection, obtained with the data of first ones, and the results of the application of the EVT to the data of the second inspections.

To apply the Bayesian inference, the a priori distributions of α and β were needed, thus, to obtain them the dataset of Table 1 has been used as described in Section 4. The best fitting for the curves α vs. t and β vs. t

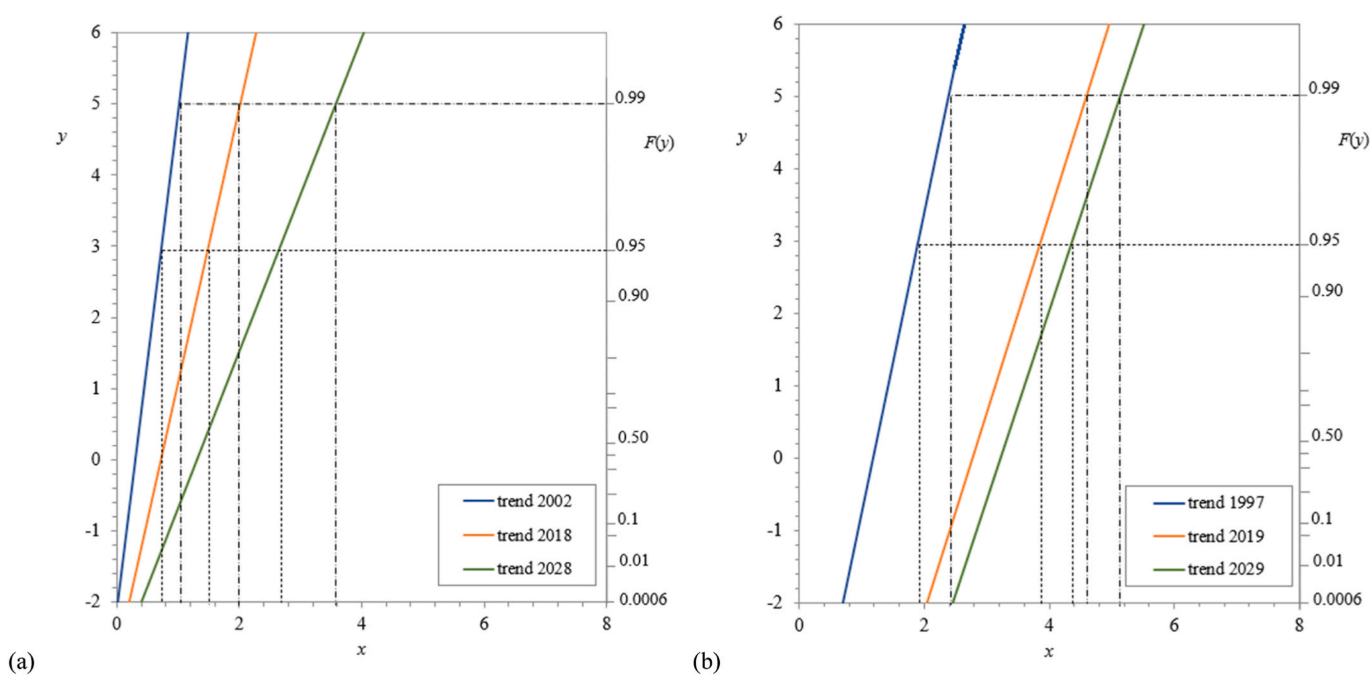

Fig. 8. Actual plot positions and forecast: (a) Tank A and (b) Tank B.

Table 7
Forecasts (parameters of the distributions and probability of the critical pit).

Tank A	
Parameter	2028
scale parameter α	0.454
location parameters β	1.310
probability critical pit ($x > 5$ mm)[a]	0.114
Tank B	
Parameter	**2029**
scale parameter α	0.382
location parameters β	3.213
probability critical pit ($x > 5.2$ mm)	0.005

[a] Value obtained by means of equation (3).

was given by a power function with two parameters. By overlapping all temporal trends of the scale and position parameters it was possible to determine the a priori probability distributions of α and β respectively after 16 years for Tank A and 22 years for Tank B i.e. the year of the second inspections. The posteriori distributions have been obtained by means of Equations (12) and (13) and are shown in Fig. 7, together with the a priori distributions. In these figures each value of α and β is representative of a class as indicated each legend. Table 6 shows the expected values of α and β at the time of the second inspection for both tanks.

The previsions can be considered acceptable and, almost in all cases, do not underestimate the parameters of the distribution. It can be stated that the model slightly overestimated the phenomenon; however, the overestimation is about 0.05 mm in corrosion depth, corresponding to a value that is not detected during the inspections. These errors are reflected in the predictions of the probability of the critical pit and are negligible.

After verifying the validity of the forecast model, it has been applied to predict the conditions of both tanks 10 years later the second inspection (i.e. 56 years for Tank A and 64 years for Tank B). The results are shown through the plot positions of Fig. 8, while the values of α and β and the probabilities of the critical pit are shown in Table 7. For Tank A, it is observed that the 99% of pits have depth minor or equal to 2 mm in 2018, with the same probability it is expected the depth increases to 3.60 mm in 2028; whereas for Tank B the 99% of pits have depth minor or equal to 4.60 mm in 2019 and with the same probability it will increase to 5.10 mm in 2029.

4.3. Residual lifetime and time to next inspection

The plot positions for the second inspection of Tank A and B and the expected trend after 10 years (Fig. 8) have been used to estimate the *RUL* (this parameter is calculated by referring to the bottom of the tank). The evolution of the corrosive phenomenon is given in Fig. 9 by plotting the values of the corrosion depth associated with the probabilities 0.99 and 0.95 (read from the plot positions of Fig. 8) against the time i.e. the inspection year. Since it is not possible to define the evolution trend of the phenomenon because only three points per tank are available, it has been conservatively assumed linear based on the data of the last inspection and the expected trend after 10 years. The corrosion rate has also been derived as the slope of the line. The value of the *RUL* and the corrosion rates are summarised in Table 8. By referring to the date of the second inspection, the conditions are favourable for an extension of 19 years for Tank A and 12 years for Tank B with a probability of 99%.

5. Conclusions

The operators of major hazard establishments in managing ASTs must balance two opposite needs: on one side more frequent inspections are desirable to prevent leakages from the bottom, on the other one numerous inspections lead to excessive costs and unnecessary occupational risks, related to the tank reclamation and to the entrance of workers inside the vessel. The results of this study show that a more accurate assessment is possible in order to get the maximum time interval that can be applied between successive inspections, with a very low risk of bottom leakages. The proposed method has been developed by exploiting a significant and representative sample of the typical ASTs, collected in Italy in refineries and oil terminals. The robustness of the used maths has been demonstrated in the detail in the two case studies. The results make the managers confident in the method as well as the authorities that have the duty to assure ASTs' integrity according to the aforementioned European Directives.

With the new "green deal", some tanks could be used for the storage of new low-carbon fuels, while others could continue operating with traditional ones, which will survive for a few years. Furthermore, some ASTs will be out of service in a short time, due to the decreased demand

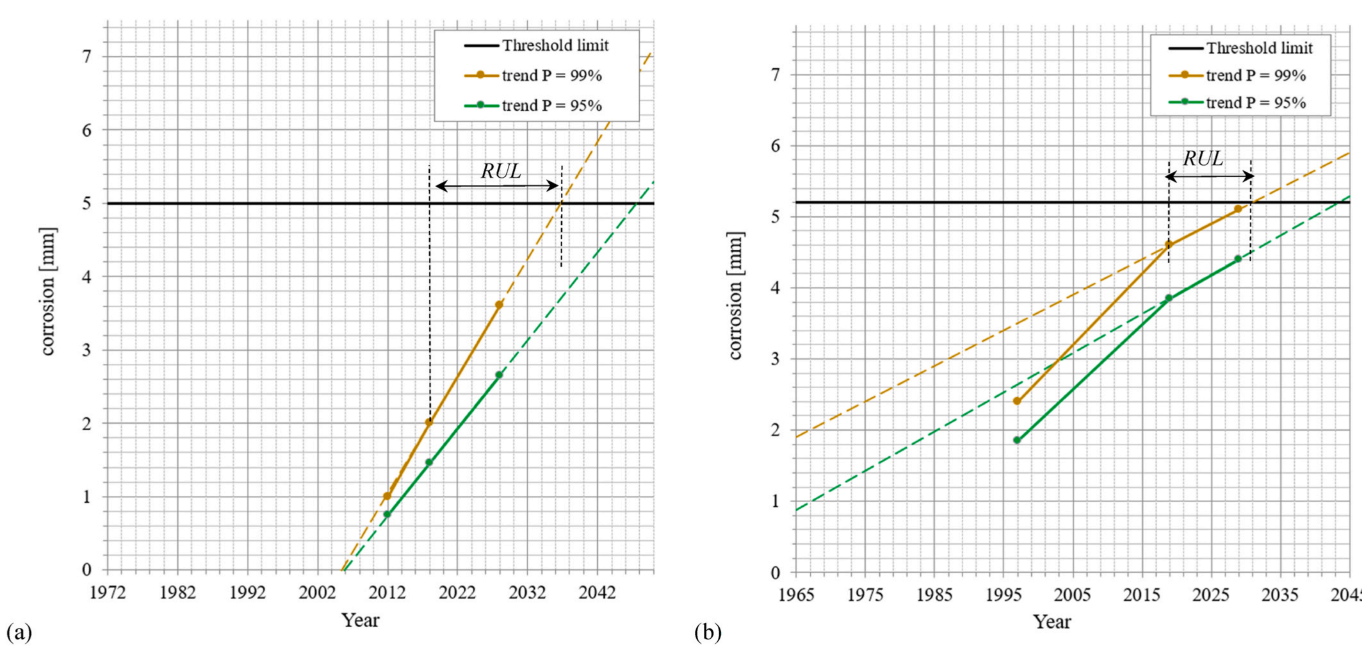

Fig. 9. Trend of the corrosive phenomenon and *RUL*: (a) Tank A and (b) Tank B.

Table 8
Forecasts (parameters of the distributions and probability of the critical pit).

Tank A		
Probability	0.99	0.95
RUL (year)	19	29
Corrosion rate (mm/year)	0.16	0.12
Tank B		
Probability	0.99	0.95
RUL (year)	12	24
Corrosion rate (mm/year)	0.050	0.055

for liquid fuels that are replaced by fuels not suitable for ASTs or directly by electricity. These circumstances imply that many old equipment will still have to be in-service for long time and accurate safety assessments of their operating will become important.

The double exponential fitting, discussed in this paper, could be suitable to describe localised corrosion for further items, including roofs and shells, annular rings and connected piping. Thus, even for those, the use of Bayesian prediction function could be essential for a more detailed evaluation of the likelihood of rupture and consequent optimal decision about time and mode for planning integrity inspection and monitoring. In the current Seveso practice, the mandatory quantitative risk assessment deals with random ruptures of tanks and pipes and uses frequency taken from the API standard or other technical sourses and correction factors (management factor and damage factor). The use of double exponential and Bayes formula could lead to a much more realistic and precise frequency evaluation and, consequently, to more effective actions to control the hazard of major accident in chemical and petrochemical industry.

Author statement

Maria Francesca Milazzo: Methodology, Supervision; Writing – original draft, Writing- Reviewing and Editing. **Giuseppa Ancione**: Methodology, Data curation, Software, Writing – original draft. **Paolo Bragatto**: Methodology, Data curation, Writing – original draft. **Edoardo Proverbio**: Methodology, Supervision; Writing – original draft, Writing- Reviewing and Editing

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jlp.2022.104781.

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