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Simplified Modelling of the Remaining Useful Lifetime of Atmospheric Storage Tanks in Major Hazard Establishments

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In Europe, after the Directive 2012/18/UE entered into force, the operators of establishments at major hazard accident are required to evaluate and manage equipment ageing through a detailed planning with the aim to control the integrity and prevent unwanted losses of hazardous materials as well as occupational risk. It is essential to estimate the equipment health and predict its remaining useful lifetime. Reliable estimates make possible to achieve a safe and efficient conduction of normal operations. To contribute to the achievement of these aims, a system is being developed, which is based on prognostic modelling and augmented reality for the prediction of the equipment degradation and the remaining useful lifetime. The system consists of hardware and software, in which the forecasting models draw information from a network of sensors installed on the equipment and from a database containing the history of inspections. The model integrates also information about deterioration mechanisms. This paper presents a preliminary study carried out for the derivation of the degradation model with respect to the mechanisms affecting atmospheric storage tanks, namely the internal corrosion of metal structures exposed hydrocarbons and the backside corrosion of the bottom floors. A comparison between the proposed method and the EEMUA standard is also given.

1. Introduction

The issue of ageing become relevant in Europe due to the evidence that most equipment of several Seveso establishments were installed more than forty years ago (Horrocks et al., 2010); in addition, worldwide reports show a significant percentage of losses of containment due to deterioration mechanisms (Wood et al., 2013; Semmler, 2016; Gyenes and Wood, 2016; OECD, 2017). Given that these installations are approaching or already reached their design lifetime, a proper monitoring and inspection planning is very important to prevent undesired consequences of ageing, namely releases of hazardous materials (Palazzi et al., 2017), as well as occupational risks (Directive 2012/18 /EU). After the Directive 2012/18/UE, operators of establishments at major hazard accident are required to evaluate and manage equipment ageing through the definition of a detailed management plan (Milazzo and Bragatto, 2019). The estimation of the equipment health and the prediction of its *remaining useful lifetime* (RUL) are essential for a safe in-service conduction, an efficient predictive maintenance and an extension of the operational lifetime. To achieve these aims, prognostic models are needed, as well as monitoring data and equipment history. Today, the combination of some innovative technologies allow exploiting prognostic models to achieve the above objectives. Available technologies include IOT solutions for smart identification of equipment, smart sensors and cloud computing to store and manage huge amount of equipment data.
Currently, a system is being developed to contribute the previously highlighted goals. It consists of hardware and software (Milazzo et al., 2019) and the core is the forecasting model, which integrates information about the deterioration mechanisms affecting the equipment, data collected thought installed sensor networks and the inspections' history from internal databases. This paper presents the derivation of the degradation model with respect to the mechanisms affecting storage tanks, namely the *internal corrosion* of metal structures exposed to hydrocarbons and the *backside corrosion* of the bottom floors. The *internal corrosion* is due to the presence of dissolved oxygen or water inside the product, as well as other impurities. The *external corrosion* is

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due to bad water drainage, stagnation around the base, infiltration of groundwater, chlorinated compounds in foundations, poor coatings and stray currents. According to Wood et al. (2013), about 15% of corrosion related accidents in refineries involves storage tanks. Integrity measurements of the bottom of atmospheric storage tanks can only be performed when the tank is empty. Acoustic emissions, already tested in research projects (Demichela, et al., 2019), could be useful for checking the presence of ongoing degradation in operating tanks, but they are absolutely complementary to direct thickness measurements. During planned shutdowns, the entire bottom is carefully examined. Currently, the best available technique is the floor-scanner, an apparatus detecting the magnetic flux leakage (MFL). It is able to detect cracks and metal losses with adequate accuracy. Spot ultrasonic thickness measurements (UTM) are still very important, as these usually integrate MFL detections in points difficult to be analysed; in addition, UTM widespread measurements are still the best solution where MFL cannot enter into the tank. The indirect costs of a complete bottom screening are independent on the techniques and, anyway, they are very high, as the tank must be put out of service for a long time, emptied and washed; then workers, including inspectors, have to stay for a long time in a highly hazardous environment. Thus, the typical inspection interval is 10 years but extension up to 20 years are accepted in the current practice in Europe and US. These can be reduced in order to ensure that the average time, before unacceptable conditions are reached (with reference to the minimum thickness), is much less than the time to the next inspection. Based on common practices (EEMUA, 2014; API), the corrosion rate is estimated as the ratio between the thickness decrease and the interval of detection and is used to forecast the RUL and to plan appropriate maintenance aimed at the prevention of leakages. Unfortunately, discrete thickness measurements cannot determine the maximum depth of the corrosion at the bottom floors, where usually materials exhibit localised corrosion in the form of pits. For this reason, it is important a stochastic modelling of the phenomenon, in order to assess the risk of perforation of the storage tank. To this scope the use of extreme value theory is frequent (Velázquez et al., 2009). The literature shows several applications of statistical approaches based on the extreme value analysis: Joshi (1994) characterised corrosion data obtained from ultrasonic testing of the floor plates of aboveground crude oil storage tanks; Shibata (1991) determined the optimum return period and predicted the maximum corrosion from a Gumbel plot; Kasai et al. (2016) combined the extreme value analysis and the Bayesian inference for the prediction of the maximum depth of corrosion. A probabilistic approach with the use of a stochastic modelling of the phenomenon could be useful for a more rigorously understanding of the reasonableness of the approaches adopted by the common practices, especially when these can be integrated with a few punctual thickness measurements. It is even better if the integration of partial or indirect measurements is possible during the normal equipment operations, by means of a network of acoustic emissions (AE) sensors. The aim of this work is to estimate the degradation rate of atmospheric tanks and their residual useful lifetime, by means of an analysis of the stochastic ageing behaviour of the bottom floors obtained by collecting UTM. The paper is structured as follows: Section 2 describes both the traditional and proposed methodology for the degradation modelling and the estimation of the RUL; Section 3 presents the case-study; Section4 provides some results and discussion; finally, Section 5 gives the conclusion of the work.

2. Methodology

2.1 Common practices

The time between two inspections of atmospheric tanks cannot be short, as each inspection requires to completely empty and clean them, causing economic implications due to the equipment unavailability, as well as impacts on the occupational safety due to need to intervene in confined and polluted spaces. In the current practices, inspection intervals up to 20 years are accepted, based on very conservative approach. According to EEMUA (2014), the RUL for tanks is correlated to the time for next inspection (Δt) as in the following:

$$RUL = \frac{s_t - s_a}{r} \tag{1}$$

$$\Delta t = K \cdot RUL \tag{2}$$

where: s_t is the thicknesses measured at the time t; s_a is the minimal allowed thickness; r is the corrosion rate; K is a confidence rating factor.

Corrosion is usually assumed to be a linear process. This is a reasonable assumption for uniform corrosion, but it is not valid for local corrosion and pitting. The generic corrosion rate is derived from worldwide databases, however, reference values for the most common used materials and products are provided by EEMUA (2014), as well as by API (2016). Temporal series of thickness measurements are essential to tune deterioration rates with a cautionary approach. The factor K is lower than 1 and takes into account all risk factors, including uncertainties. It deals also with the pitting by means of a further factor to be included in K.

A probabilistic lifetime assessment accounting for the stochastic aspects of the local thinning of the plate floor (including pitting) is useful to more rigorously understand the reasonableness of the approaches adopted by common practices. However, if the probabilistic evaluation relies on a few punctual thickness measurements, performed every 10 or 20 years, there will be a certain advantage over the empirical evaluations described above. A further advantage could come from the integration of partial or indirect measurements, performed during in-service periods of the tank by means of AE, which some fairly extensive experimental campaigns have shown to be able to detect energy releases due to the loss of material from the bottom of the tank.

2.2 Proposed approach

To estimate the degradation rate and the RUL of atmospheric tanks, the proposed approach combines the extreme value analysis, used with the block maxima approach, and the Bayesian inference to elaborate data collected during inspections with the UTM. The Gumbel distribution (Gumbel, 1958) is used to estimate the maximum depth in a large surface area from which small area are inspected, it is the following:

$$F(x) = \exp\left(-\exp\left(-\frac{x-\beta}{\alpha}\right)\right) \tag{3}$$

$$f(x) = \frac{1}{\alpha}\exp\left(-\frac{x-\beta}{\alpha}\right)\cdot\exp\left(-\exp\left(-\frac{x-\beta}{\alpha}\right)\right) \tag{4}$$

where: x is maximum corrosion depth; $F(x)$ and $f(x)$ are respectively the cumulative probability function and the density probability function; α and β are respectively the scale and the location parameters of the distribution.
By introducing a reduced variate (y), the following equation is used to construct the Gumbel probability plot:

$$y = -\ln\left(\ln {}^{1}\!/_{F(y)}\right)\ , \quad y = \frac{x-\beta}{\alpha} \tag{5}$$

The cumulative probability can be calculated simply by the following equation:

$$F(y) = \frac{i}{N+1} \tag{6}$$

where i = rank number; N is the total number of measures.
By plotting y as a function of x, a straight line is obtained; its slope and intercept provides $1/\alpha$ and $-\beta/\alpha$. A distribution with large α has a long tail meaning the occurrence of localised corrosion. The location parameter β is the mode of the corrosion distribution. To predict the maximum depth of corrosion by extreme value analysis with the Gumbel plot, the scale parameter, the location parameter and the $F(y)$ are required.
While α is associated with the degradation mechanism, the position β represents the most frequent maximum depth value of the distribution and should move towards higher depths. Hence, to estimate the backside corrosion rate and the expected RUL for atmospheric tanks, by using the detected maximum corrosion depth by UTM, the Bayesian inference can be applied to determine the posteriori probability distribution of β:

$$\lambda''(\beta\,|\,x) = \frac{\lambda'(\beta)\cdot f(x\,|\,\beta)}{\int \lambda'(\beta)\cdot f(x\,|\,\beta)\cdot d\beta} \tag{7}$$

where: $\lambda'(\beta)$ and $\lambda''(\beta|x)$ are the prior and posterior probability distributions of β after a given period of usage of the storage tank; and $f(x|\beta)$ is the likelihood function.
The new value of the location parameter, after the Bayesian inference, makes possible to drawn the expected plot position from which it is possible to determine the corrosion rate and the trend of the RUL.

3. Case-study

The case-study refers to a large fixed roof atmospheric tank, used for the storage of different light aromatic solvents (e.g. naphtha solvent). The tank has a maximum capacity of about 5000 m^3 and it has been in-service since 1962 in a Seveso site, included in an area featuring residential buildings, highways and railways, as well as natural vulnerable elements (a creek and a beach). The study focused on the tank bottom, which is critical because even a modest leakage could pollute, through the groundwater, the creek, the beach and the sea with high remediation costs. The bottom is made by 53 carbon steel plates, welded each other to cover an area of about 360 m^2. The nominal thickness is 8 mm. In the last decade, it was inspected twice seven years apart. Before the inspections, it was emptied and cleaned. Inspection protocol included an extensive visual inspection, a complete leakage control and a number of UTM for each plate of the bottom. The use of the MFL was not possible because the tank configuration. The basic parameters of these inspections are given in Table 1. Corrosion was quantified as the difference between the nominal thickness and the measured thickness.

Table 1: Basic inspection parameters.

ID inspection	Year	No. points	Average thickness	Standard deviation	Minimum thickness
1	2010	126	5.90	0.30	4.7
2	2017	252	5.79	0.23	3.9

4. Results

The set of the maximum corrosion depths at each plate was analysed. A Gumbel plot of the cumulative probability versus the backside corrosion was produced by using data of 2010 and 2017 (given these were the most recent available data) and the regression line was obtained (Figure 1). The parameters of the distribution are shown in Table 2.

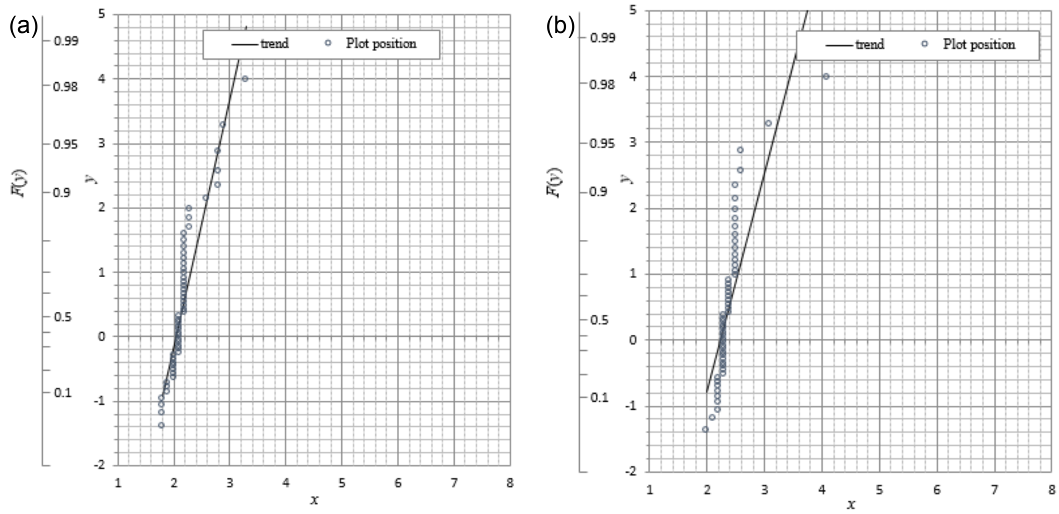
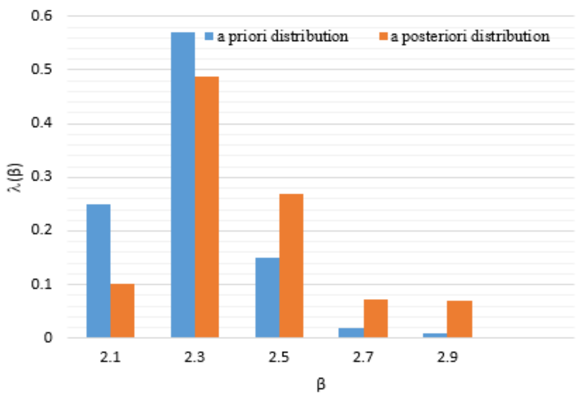


Figure 1: (a) Plot position 2010, (b) Plot position 2017.

Table 2: Gumbel parameters.

ID inspection	Year	Scale parameter (α)	Position parameter (β)
1	2010	0.261	2.041
2	2017	0.303	2.237

By comparing the inspection periods, the mode of the Gumbel distribution become greater over the last in-service period, whereas the scale parameter was slightly increased. The change of α was due to the increase of the variances of the maximum depth caused by the evolution of the localised corrosion. An increase of about 13% could reasonable be assumed each 7 years (linear trend extrapolated from data 2010 and 2017). The UTM of 2010 were used to predict the maximum depth of corrosion for 2017, then, those of 2017 verified the consistency of the results.To apply Eq. (7) the knowledge of the expected a priori distribution for β after further 7 years of usage of the tank was required.



β	classes of β
2.1	2.0≤β<2.2
2.3	2.2≤β<2.4
2.5	2.5≤β<2.6
2.7	2.6≤β<2.8
2.9	2.8≤β<3.0

Figure 2: A priori and posteriori distributions for the position parameter.

Due to the lack of literature data, a distribution was defined by analysing the evolution of the thicknesses of the tank according to the API standard. The x parameter in Eq. (7) is the highest maximum depth value in 2010, i.e. 3.3 mm. The a priori distribution of β is given in Figure 2, where each value is representative of a class; in the same graph also the elaborated posteriori distribution is shown. The expected β after 7 years of usage was 2.40, by using this value it was possible to predict the evolution the corrosion at each plates.
Figure 3(a) shows the plot position for 2010 and 2017 and the expected trend for 2017. It is observed 94 % of pits have depth minor or equal to 2.8 mm, with the same probability it is expected the depth increases to 3.2 mm in 2017. The 2017 plot position was used to validate this forecast and the real corrosion at the same point is 3.15 mm. It could be seen that the forecast overestimated the phenomenon and the minimum overestimation is about 0.05 mm, corresponding to a depth that was not detected during the UTM. Hence, a more accurate measure appears important for the applicability of the method. The estimation of the RUL is made in Figure 3(b) by reporting the evolution of the corrosive phenomenon as observed in Figure 3(a), from this it was also possible to derive the corrosion rate, which is the slope of the line associated to each plate (about 0.4 mm/y).

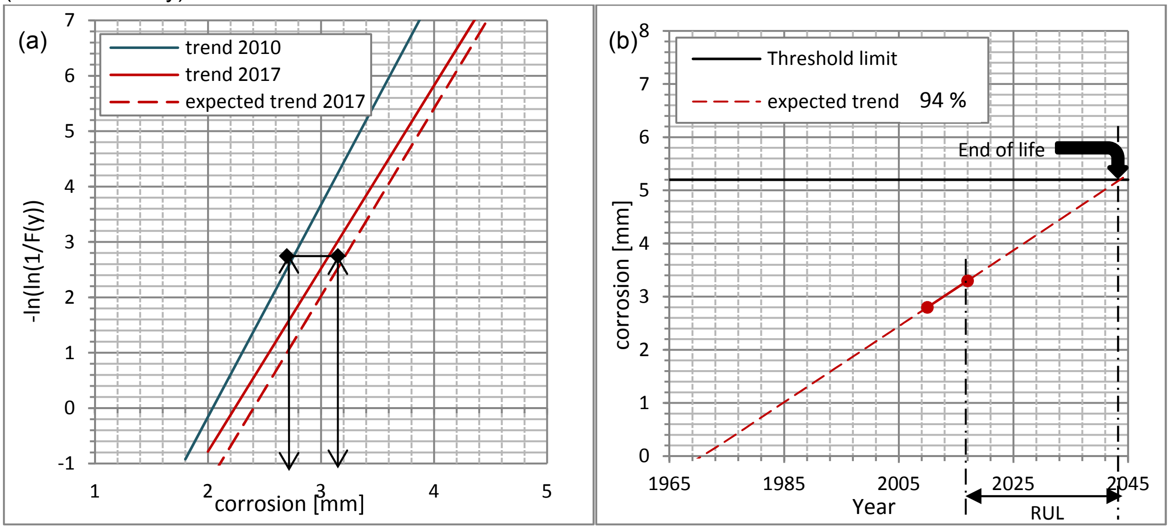


Figure 3: (a) Plot position and forecast; (b) Residual useful lifetime.

The corrosion rate was compared with the value obtained with the EEMUA standard. The results are summarised in Table 3. The corrosion rate (r) was comparable (even a bit lower) than r reported by EEUMA for carbon steel and solvent (0.15 mm/y). The value was adjusted to take into account the pitting effects. The EEUMA method is based on different check lists for bottoms, shells and roofs. It uses a 4 level to rank both likelihood and consequence of losses (*negligible*, *low*, *medium*, *high*). The resulting ranking from the application of the check list to the bottom of the tank was *high* for consequence and *medium* for likelihood. Further credits or penalties were added to consider the inspection techniques. The visual inspection integrated by spot UTM has penalty equal to – 0.1. This evaluation is very conservative and the spread of thickness measurements implies a high uncertainty. In addition, if the average thickness was used despite the method, the r would be twice and half lower and the time to next inspection 10 years. Thus, the method recognised in the current engineering practice, is questionable indeed and a less rough and conservative approach is highly desirable.

Table 3: Results of the application of EEUMA method.

Initial data		Outputs		Outputs	
Minimal thickness 2010	4.70 mm	Corrosion rate r	0.11 mm/y	Likelihood rating	*medium*
Minimal thickness 2017	3.90 mm	Pitting factor	1.05	Confidence factor K	0.5
Thickness allowance	2.5 mm	Adjusted r'	0.12 mm/y	Credits/Penalties	0
Safety margin	0.2 mm	RUL	10 y	K'	0.5
Inspections interval	7 y	Consequence rating	*high*	Time to next inspection	6.1 y

5. Conclusions

The proposed method provides less conservative and site-specific information that the EEMUA standard, as it uses data collected at each inspection. The calculated corrosion rate is very close to that obtained by the API standard, which is less conservative than EEMUA. The probabilistic assessment of the RUL allows the operator planning in a more flexible way the date of the next inspection. Thus, he/she is able to better balance the opposing needs (integrity versus occupation safety), i.e. to ensure the equipment integrity over the time and to minimise the effects on occupational safety due to interventions inside the tank. In addition, given that the monitoring with AE technique can identify areas where corrosion is more active, providing valuable information for more effective ultrasonic thickness measurement or localising possible product leaks, its combination with the proposed approach allows exploiting in more effective way the prognostics for the management of safety.

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