Estimation of the Equipment Residual Lifetime in Major Hazard Industries by Using a Virtual Sensor

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Prognostic is central in the management of components and production systems, structures and infrastructures. It aims estimating their health status and predicting residual useful lifetime, based on data and information related to degradation processes, the normal plant operability and the environmental conditions. Trustable estimates of the residual lifetime for systems allow achieving several goals, including a safe conduction of operations, an efficient operability that allows predictive maintenance actions and the extension of operational lifetime, under safety conditions. This point is particularly important in the context of the chemical and process industry, that is subject to the Seveso Directive. This normative recently imposed the plant operator to assess and manage equipment aging by redacting a detailed aging management plan. As a consequence, methods and tools are being developed for the assessment and management of deterioration mechanisms at major hazard industries. This paper presents the results related to the development of a virtual sensor for the estimation of the residual lifetime of the industrial equipment. In the initial version, the virtual sensor uses simplified models for the aging forecasting and information collected during audits and the equipment monitoring. Preliminary results of the implementation and testing of the initial version of the virtual sensor are shown by means of its application to a case-study.

Keywords: Aging, Major hazard industry, Inspection, Damage mechanism, Residual useful lifetime, Virtual Sensor.

1. Introduction

Most chemical and process industries, falling under the European Seveso III Directive on the control of major accidents (EU Council, 2012), have been commissioned in the Sixties or Seventies. For this reason, the in-service time of most process equipment largely exceeds the limit assigned during the design phase (Milazzo and Bragatto, 2019). Such an extension may be reasonable as inspection techniques and maintenance procedures have been continuously improved during these last fifty years. Nevertheless, it is essential to question how long the operator can extend the lifetime of a component without jeopardize the safety of the plant. Process equipment (so-called *critical equipment*) includes primary containment systems (e.g. atmospheric tanks, pressurized vessels), machinery (e.g. pumps, compressors), control and safety systems (e.g. instruments, actuators). It has to be distinguished that an aged machine may be replaced as well as an obsolete control system, whereas the replacement of large process equipment (e.g. a vessel) is often unfeasible because of the costs, the impact on other activities and the required authorizations. Moreover, even though a containment system is not yet close to the end of its design lifetime, the estimation of a reliable expected time for a safe service is anyway essential. A trustable prognosis for each equipment is a keystone for an effective, profitable and safe management of the overall plant. Prognostic is essential to implement a maintenance policy based on actual current and future conditions (on-condition predictive maintenance), which largely increases the plant operability (Jardine et al., 2006; Elwany and Gebraeel, 2008; Wang and Hussian., 2009).

According to common practices (API, 2016a; API 2016b; ISO, 2014), the *mean time before a failure* (MTBF) for a piece of equipment is predicted based on generic statistic data not up to date. Pittiglio et al. (2014) discussed the limits of generic failure rates in the public domain, commonly used by industrial practitioners. This causes that estimates are affected by a high uncertainty (Milazzo and Aven, 2012). In addition, the effects of different inspection and maintenance frameworks are not accounted for, neither the benefits of safety procedures, including risk assessment, training and personnel resources, operating control and management of changes. In case of containment systems, major "failures" are related to the loss of mechanical integrity (e.g. cracks, holes, ruptures) of the structure, which may cause the release of hazardous materials, eventually, escalating in severe accidents (OECD, 2017; Palazzi et al. 2017; Wood et al, 2013). Thus, the uncertainties, associated with the statistical approach, compel the operator to be precautionary. To this scope

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many regulations have fixed mandatory inspection intervals for pressurized equipment. Currently well-defined approaches for the optimization of test intervals, by accounting for highly uncertain aging parameters or maintenance effectiveness, are available; these are applied in the nuclear context and more recently in the chemical and process industry (Kančev et al., 2011; Martón et al., 2015; Biondi et al., 2017).

Predicting how long an individual system can be used without any loss of containment becomes a challenge and is essential to maximize the in-service time and, consequently, minimize the costs for the asset management. The term *prognosis* is commonly used with a meaning similar as in medicine: but in this context, inspections provide data for the diagnosis about the actual health condition of equipment, even if a detailed information and a sound knowledge are essential in order to have a trustable diagnosis. This is particularly relevant in the context of the chemical and process industry, in which the cited Directive Seveso III imposed the plant operator to assess and manage equipment aging by drawing up a detailed aging management plan for establishments at major hazard. As a consequence, methods and tools are being developed to support these activities; these are here classified as methods for fault diagnosis (see e.g. Ragab et al., 2018; Diez-Olivan et al., 2019) and approaches for assessing and managing aging (see e.g. Candreva and Houari, 2013; Thomson, 2015; Bragatto and Milazzo, 2016).

This paper presents the results related to the development of a virtual sensor for the estimation of the residual lifetime of the industrial equipment. The virtual sensor is composed by software and hardware. In its initial version, the virtual sensor uses simplified models for aging forecasting and information collected during audits and from the equipment monitoring. Models refers to concepts that are already defined in the literature, but they were adopted for the purpose of this study. Some innovative technologies have been combined to support the application of these models, i.e. IOT technologies for a smart identification of equipment and cloud computing to store equipment data. Some preliminary results of the implementation and testing of the initial version of the sensor are shown in this contribution by means of its application to a case-study. The paper is structured as follows: Section 2 describes models for the assessment of aging through some metrics, including also the *residual useful lifetime* for industrial equipment and the system for the visualization of results (the *viewer*); Section 3 presents the case-study, which has been used to test the virtual sensor; Section 4 shows the preliminary results of the application; finally, Section 5 gives some conclusive remarks and future perspectives.

2. Models and technologies

To estimate the *residual useful lifetime* of industrial equipment based on its actual health conditions, the combination of models for aging assessment with some innovative technologies (Bragatto et al, 2018) is proposed in this paper. As mentioned above, these enabling technologies includes technologies for a smart identification of equipment (Gnoni et al., 2016) and cloud computing to store and manage equipment data and outputs deriving from the quantification of the aging conditions of equipment (ageing metrics).

The issue of equipment aging in major hazard sites has been developed by the Seveso III Directive. Recently, an index method has been adopted by the Italian regulators, whose theoretical basis and the details have been discussed in depth by Milazzo & Bragatto (2019). This method supports the industrial operator in dealing with the task of assessing aging and defining measures to contrast it, which will be preliminary for drawing up a detailed aging management plan, in accordance with the requirements of the legislation. Basically, the method is a *fishbone model*, which considers factors that accelerate ageing processes and factors able to decelerate them, thus promoting longevity. Accelerating factors include age/in-service time, stops, failures, accidents/near-misses, defects/ damages and deterioration mechanisms (e.g. corrosion, erosion, creep, etc.). Deterioration mechanisms are weighted according to detectability, velocity and consequence criteria. Longevity factors include physical factors (process control and physical protection) and organizational ones (audit, integrity management system, adequacy controls and inspection results). All input parameters to the model are measurable quantities; whereas, the output of the method is a score ($I_{overall}$) applicable to a unit of the establishment or to the whole industrial site. The rules for assigning the score to each factor (according to which the output is calculated) have been derived from the judgment of a working group, composed by experts about the topic and including representatives from control bodies, industrial operators and academia.

The following sections describe the models, which have been adopted for the calculation of the aging status of the equipment and for the future forecasting about its conditions. They have been implemented in the virtual sensor. All models refer to the *fishbone method*, mentioned above, hence, they include both the aging and longevity factors, defined by Milazzo and Bragatto (2019).

This also means that all factors flow into the three-following metrics:

- Aging-longevity indexes
- Frequency of failure/loss of containment
- Residual useful lifetime

2.1 *Aging-longevity indexes*

Accelerating and longevity factors, with respect to aging, are combined into an index representing the aging status for the equipment, the unit or the establishment, as extensively discussed by Milazzo and Bragatto (2019). This index is calculated in two steps by assigning a score to each factor, on a scale ranging from 1 to 4 (1 = low; 2 = medium; 3 = medium-high; 4 = high), and averaging all factors by considering accelerating (a_i with $i = 1, ..., n$) with a negative sign and longevity ones (l_j with $j = 1, .., n$) with a positive sign. This process gives an average index for aging and an average index for longevity:

$$I_a = mean(a_i) \tag{1}$$

$$I_l = mean(l_j) \tag{2}$$

where: a_i = accelerating factor; l_j = longevity factor.

By means of a comparison between these two indexes, it is possible to make considerations about the management of deterioration mechanisms. Results could also be given in the form of an overall index ($I_{overall}$):

$$I_{overall} = I_l + I_a \tag{3}$$

Final indexes could be positive or negative depending on the absolute of I_l and I_a, i.e. if $| I_l | > | I_a |$ the management of deterioration mechanisms allows contrasting them, whereas if $| I_l | < | I_a |$ is the opposite situation.

2.2 *Frequency of failure/loss of containment*

In this study the metric *frequency of failure* has been defined as the likelihood of occurrence of an event leading to a loss of containment (so-called *random rupture*). The approach, suggested for the quantification of the frequency of failure for the equipment due to aging is inspired by Milazzo et al. (2010) and is based on three steps:

(i) the definition of relationships between prevention measures of accidents due to aging, adopted by the Company, and factors affecting the phenomenon;

(ii) the estimation of weight coefficients for aging/longevity factors to be used for the modification of the general frequencies, taken from international databases (e.g. HSE, 2012; OREDA, 2015) and commonly used in QRA.

(iii) the modification of the frequencies of failure, according to a model proposed by Papazoglou et al. (1999).

Thus, the application of the method consists of auditing each unit of the establishment with the aim to identify the causes of failure due to aging and the measures that can prevent them. The weight coefficients for the causes of failure, which are used to apply the method, are the percentages of failures and relate to each unit of the establishment.

The model for the modification of the frequency, given by Eq. (4), has been obtained by analysing data of incidents in chemical industry. It shows that the frequencies of release from various equipment spans two orders of magnitude and has certain symmetry around the average values (Papazoglou et al., 1999):

$$\log f_{mod} = \log f_{average} + \sum_{i=1}^{n} \frac{w_{ai} x_{ai}}{100} + \\ + \sum_{j=1}^{n} \frac{w_{lj} x_{lj}}{100} \tag{4}$$

where: f_{mod} = modified frequency of failure (frequency of loss of containment); $f_{average}$ = average frequency of failure based on world-wide experience; w_{ai} = weight assigned to the factor a_i in contributing to aging; w_{lj} = weight assigned to the factor l_j in contributing to longevity; x_{ai} = normalized score assigned to a_i; x_{lj} = normalized score assigned to l_j.

In Eq. (4), the score x assumes the following values: - 1 if the effect on aging management is judged GOOD; 0 if it is judged AVERAGE; + 1 if it is judged POOR. Therefore, given that the score from the fishbone model range from – 4 to + 4, a normalization was needed to bring back the values to the scale – 1 to +1.

2.3 *Residual useful lifetime*

A useful parameter for the plant operator is the *residual useful lifetime* of the equipment under the impact of aging/longevity factors. Longevity factors act by counteracting the loss of integrity of the equipment and, thus, extending the remaining lifetime, while the aging factors are those that reduce it. Both technical and the operational integrity should be safeguarded to prevent undesired consequences (major accidents). This can be achieved by monitoring and inspecting the system, through the use of suitable techniques. If recorded measurements are few, a graphical plot may indicate a constant degradation rate but, in reality, the degradation rate may vary over time.

This aspect should be considered and often *worst-case* assumptions are made to provide acceptable safety margins. Through inspection, the average rates of degradation may become better defined.

The assessment of the remaining useful lifetime of a system or a component is essential for inspection planning. According to EEMUA (2014), this is done by using the *degradation rate* and the *degradation allowance*, as derived from the relevant design and repair codes and operating conditions. *Remaining useful lifetime* (*RUL*) for tanks is defined as:

$$RUL = A_{degradation} \,/\, R_{degradation} \tag{5}$$

where: $A_{degradation}$ = degradation allowance that represents the level permitted for the damage, which can be expressed by a thickness or others; $R_{degradation}$ = rate of degradation.

In general, the risk rating, derived from the assessment of the degradation process of an item, is used to determine next inspection date as a fraction (K) of the remaining life. Therefore, the inspection interval can be calculated as:

$$\Delta t_{inspection} = K \cdot RUL \tag{6}$$

where: $\Delta t_{inspection}$ = inspection interval.

The confidence rating factor K ($0 < K \leq 1$) reflects the confidence that the RBI team has in the assessment of remaining lifetime. K is dependent on the following:

- actual risk rating of the particular tank component;
- judgement regarding the stability of the degradation mechanism and the methods for its control;
- quality of previous inspection data;
-
- quality of the inspection/monitoring techniques to be used for future; (in-service) inspections (which includes establishing degradation rates);
- number of inspections carried out;
- previous inspection interval;
- whether preventive measures are in place.

The initial values of K are chosen from experience and by taking into account the classification for consequence and frequency suggested by RBI. Table 1 shows suggested values.

Table 1. Value assigned to confidence rating factor K from risk rating.

Frequency rating ⇓	Confidence rating factor K			
High	0.8	0.6	0.5	0.5
Low	0.8	0.7	0.6	0.5
Medium	0.9	0.8	0.7	0.6
Negligible	0.9	0.9	0.8	0.7
Consequence rating ⇒	Negligible	Low	Medium	High

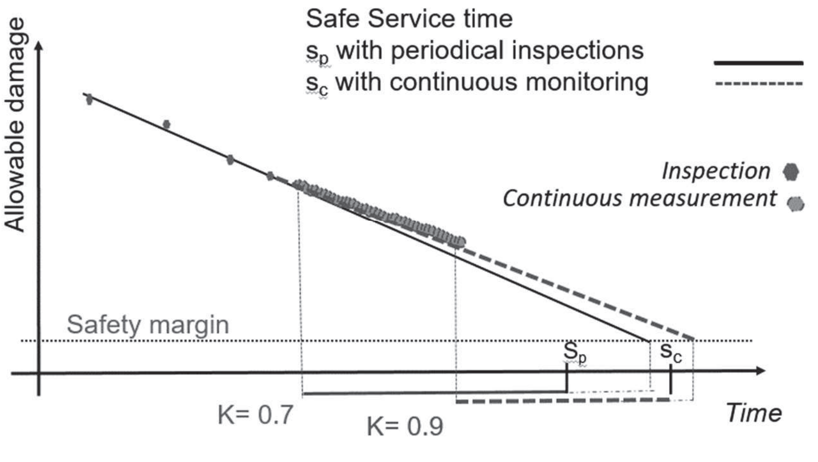

Fig. 1. Trend of allowance degradation (e.g. thickness) over the time with periodical inspections and with continuous monitoring.

Figure 1 shows the trend of the degradation allowance assuming periodical inspections (curve Sp) and continuous monitoring (curve Sc), reference has been made to a corrosion phenomenon. A linear damage (corrosion) rate has been assumed in this figure. The extrapolation of the measurement, made at time t_o, intercepts the safety margin level at a time t. By using a continuous monitoring, the forecast of the *RUL* is always updated based on the measurement. The line related to safety margin allows controlling the degradation.

2.3 *The viewer*

The resulting *RUL*, computed according to the described algorithms, is represented on a wearable viewer and can be directly consulted during a walk inside the establishment (Milazzo et al., 2019). The viewer is a part of the virtual sensor. By using such a sensor, it is sufficient for the inspector to approach a vessel or a pipeline and, through a smart label, the equipment is recognized. Then, relevant information is retrieved and merged with the data measured in real-time by the continuous monitoring sensors. Thus, the inspector has on his/her wearable viewer a trustable and up-to-date diagnosis on the *RUL* and the safe service time.

3. Case-study

The case study is a depot of liquid fuels, located close to Rome. The jet-fuel storage and the pipeline units have been considered. The jet-fuel storage unit includes two large floating roof tanks (TK2 and TK5) having a capacity respectively of 25.000 and 10.000 m^3) and two extraction and induction 6" pipelines. Three 12" pipelines reach the pipeline unit, connecting port, airport and refinery; this unit includes also pumps and a 150 m^3 booster, serving the pipelines.

The tanks are regularly inspected according to the standard EEMUA 159 (EEMUA 2014). Inside the investigated site, tanks and pipelines have a service age of 44 and are very close to the end of their design lifetime. A minimal extension was accorded, because the actual corrosion rate has been verified to be lower than expected. Namely TK2 and TK5 have a design lifetime, based on precautionary assumptions about the corrosion rate, respectively of 42 and 53 years. The main damage mechanism is soil corrosion, which could cause a bottom oil leakage, with severe consequences for both environment and safety. The site is periodically inspected on behalf of the Competent Authorities according to the Seveso legislation. In November 2018, the *fishbone method* has been applied, the aging and the longevity indexes have been obtained as a basis to simulate the condition of the equipment under the following different assumptions:

- Assumption 1: no intervention.
- Assumption 2: The 12" pipelines are provided with a UT (ultrasounds) commercial continuous monitoring system.
- Assumption 3: TK2 is provided with a continuous EA monitoring system, based on an innovative acoustic emission technology, developed in the framework of the SmartBench project (Messina et al., 2018).

The assumption 1 makes the prognosis based on the assumed corrosion rate, i.e. conditions detected at the last inspection as well as on the *fishbone* score that is continuously updated. The monitoring will be certainly very conservative.

The assumption 2 leads to an improved prognosis for pipelines, by taking into account the thicknesses monitored by the UT sensors. There is an uncertainty degree, due to potential pitting corrosions, which could be hidden for the UT sensors.

The assumption 3 improves the prognosis also for TK2. EA is adequate to detect active corrosion phenomena, if an adequate network of sensors is applied to an atmospheric storage tank (Messina et al., 2018). As long as there is zero signal, a reasonable certainty that there are no processes in progress can be considered. When something is detected, this a signal meaning that there is a damage mechanism in progress. From the intensity of the activity it is possible to make predictions on the *residual useful lifetime* that is much more accurate than those deriving from the general corrosion rates.

4. Results

The initial aging status, determined in November 2018, has been assessed according to the *fishbone model*. The result gave a value of – 1.47/– 4.0 for the aging index and 2.83/4.0 for the longevity one. The calculation of these metrics through Eq. (1-3) is simple, as well as their comprehension. The model is based on a multifactor approach, including both technical (protections, inspections, damage mechanisms, failures, ruptures, repairs, etc.) and organizational (certifications, audit, inspections and maintenance planning) issues. The strength of the method, beyond the limits induced by the simplifications, is that it is shared by a larger community, approved by regulators and companies. Nevertheless, to use the *fishbone method,* a plenty of useful data and information must be gathered throughout the establishment. It is a pity to use them only to obtain a score for compliance purpose. The methodology has a larger potential, which could be used also to address the management of individual items, including pressurized vessels and atmospheric tanks. This consideration justifies the development of two other metrics associated with aging, i.e. the frequency of failure and the residual useful lifetime.

Tables 2, 3 and 4 show residual useful lifetime *RUL* and aging indexes calculated with the *fishbone method*, with respect to each assumption. The calculation of *RUL* is based on the thickness as measured in the last integrity inspection. The comparison of the metrics over the time allows defining measures for the detected degradation level. Table 2 considers that no intervention is made, thus metrics reflects the natural evolution of the phenomenon.

Table 2. Residual useful lifetime and aging indexes for assumption 1.

Item	Metric	Year			
		2018	2020	2022	2024
TK2	*RUL*	6	4	2	0
TK5	*RUL*	9	7	5	3
12’’Pipelines	*RUL*	10	8	6	4
6’’ Pipelines	*RUL*	10	8	6	4
Depot	I_a	-1.86	-1.91	-1.97	-2.02
Depot	I_l	2.58	2.53	2.53	2.53
Depot	$I_{overall}$	0.72	0.62	0.56	0.51

Table 3. Residual useful lifetime and aging indexes for assumption 2.

Item	Metric	Year			
		2018	2020	2022	2024
TK2	*RUL*	6	4.1	2.2	0.3
TK5	*RUL*	9	7.1	5.2	3.3
12’’Pipelines	*RUL*	10	8.4	6.8	5.2
6’’ Pipelines	*RUL*	10	8.4	6.8	5.2
Depot	I_a	-1.86	-1.86	-1.91	-1.97
Depot	I_l	2.58	2.61	2.61	2.61
Depot	$I_{overall}$	0.72	0.76	0.70	0.65

Table 4. Residual useful lifetime and aging indexes for assumption 3.

Item	Metric	Year			
		2018	2020	2022	2024
TK2	*RUL*	6	4.5	3.0	1.5
TK5	*RUL*	9	7.1	5.2	3.3
12’’Pipelines	*RUL*	10	8.4	6.8	5.2
6’’ Pipelines	*RUL*	10	8.4	6.8	5.2
Depot	I_a	-1.86	-1.80	-1.86	-1.91
Depot	I_l	2.58	2.68	2.68	2.68
Depot	$I_{overall}$	0.72	0.88	0.83	0.77

Figure 2 gives the percentage of *RUL* reduction by accounting for the aging phenomenon and the monitoring and inspecting activities. Results are shown for tank TK2 and the 12’’ pipelines.

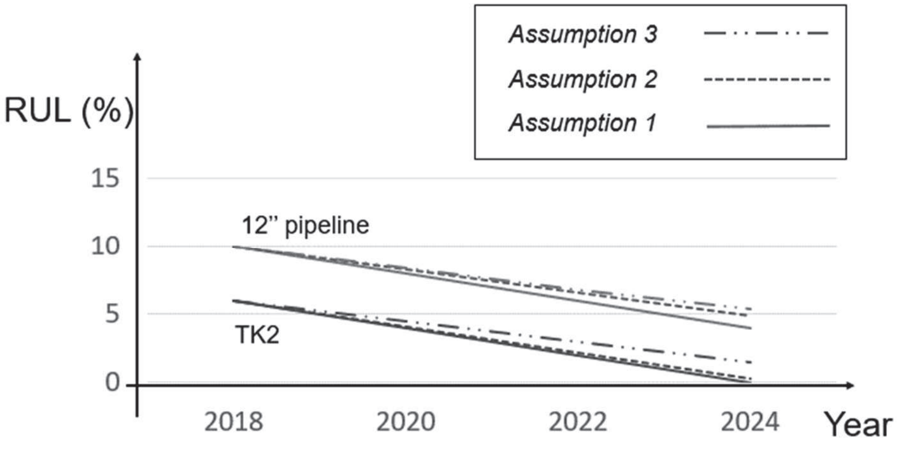

Fig. 2. Case study. Effects of the prognosis on the *RUL* due to continuous monitoring by means of commercial solutions (assumption 2) and high end techniques (assumption 3).

5. Conclusions

The results, obtained by the testing of the virtual sensor, demonstrate the feasibility of a sort of smart device revealing the actual aging of a component, in a complex site, such as a Seveso establishment. The strength of this “aging virtual sensor” is to put together the continuous measurement data with complex information about the factors driving the aging process, which are summarized by the *aging index* (as derived by the *fishbone* method used in the Italian Seveso establishments). In this way the remaining useful life of an individual component may be continuously be updated, taking into account both direct measurements and information about the operational and organizational context. The idea has been implemented and texted in a use-case, by exploiting the potential of an innovative acoustic emission wireless sensor network, developed in the research project SmartBench.

Anyway, by now, there is already a number of commercial sensors suitable to control thinning and cracking of in-service vessels and pipes, as well as sensors for monitoring rotating machines and environmental parameters. These are able to provide a large amount of data to feed the virtual sensor for ageing. Currently, further sensors, proper for the integrity monitoring, are at a higher technical readiness level and in a few years surely will enter into the common industrial practice. The proposed virtual sensor for aging is ready to include them, to provide the industrial operators with a versatile solution to analyse the conditions of the establishment, which also adapts to the various equipment types featuring different damage mechanisms.

In the use-case, the prevailing damage mechanism is the soil corrosion, as the jet-fuel contained in the tank is not corrosive. In case of different concurrent damage mechanisms, the extrapolation of the deterioration trend could need of a sounder computational model. Thus, a research effort is still required in order to extend the applicability of the proposed approach.

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