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Key Performance Indicators of aging safety barriers in oil and gas facilities

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Aging of safety barriers can degrade their performance and increase risk in Oil and Gas (O&G) facilities. Condition-informed risk assessment can be used to assess the risk of a facility given the actual performance of its safety barriers and eventually prescribe maintenance activities. In this work, we propose a novel definition of Key Performance Indicators (KPIs) of safety barriers that allows accounting for their aging. When sufficient barrier failure data are available, a Q-Weibull model is used to quantify a corrective factor that multiplies the no-aging basis KPI value. When barrier failure data are scarce, which is often the case in practice, the corrective factor is quantified by an expert-based Weibull-like distribution, that anchors some or all the different stages of barrier life (such as infant and wear-out mortality phases) with the few, limited data available. The safety barrier of Design Integrity (DI), typically employed in upstream Oil and Gas (O&G) platforms, is numerically elaborated as a practical example.

Keywords: Safety barrier, Aging, Key Performance Indicator (KPI), Bathtub curve, Q-Weibull distribution, Maximum Likelihood Estimation (MLE)

1. Introduction

Process safety incidents in Oil and Gas (O&G) facilities can cause damage to both people and the environment, and lead to large economic and reputational losses. Safety by design is pursued by implementing both preventive and mitigative safety barriers, to reduce the probability of occurrence of accidents and to mitigate their consequences, respectively (ISO 17776, Di Maio et al. 2023a, Di Maio et al. 2023b). However, aging of safety barriers can degrade their performance and lead to a larger risk. To authors knowledge, the approaches so far proposed in the literature for the assessment of safety barriers performance (to name few, simplified risk indexes (Cozzani et al., 2009), Monte Carlo simulation (Abdolhamidzadeh et al., 2010) and Bow-Tie diagrams (Cherubin et al., 2011)) still neglect the influence of the safety barrier degradation on its performance (Landucci et al., 2016).
To overcome this limitation and enable a condition-informed risk assessment (Di Maio et al., 2018) that would assess the risk of an installation given the actual performance of its safety barriers, in this work a novel definition of a Key Performance Indicator (KPI) of safety barriers is proposed. The novelty of the proposed approach consists in the definition of a time (t)-dependent corrective factor $C(t)$ that multiplies the typically adopted no-aging basis KPI value. Such corrective factor $C(t)$ is expected to well suit the typical phases of an aging system (i.e., infant mortality, useful life and wear out): when sufficient barrier failure data is available, $C(t)$ can be quantified with a Q-Weibull model (Assis et al., 2013) coupled with a numeric algorithm (in this work, the Non-dominated Sorting Genetic Algorithm (NSGA-II) (Deb et al., 2002)) to fit the model parameters to the data; when, in practice, barriers failure data is usually not sufficient for a proper fitting of the Q-Weibull model, an expert-based Weibull-like distribution is instead used to anchor some (or all) the different stages of barrier life with the few, limited data available.
In this work, we consider as case study the preventive safety barrier of Design Integrity (DI), typically employed in upstream Oil and Gas (O&G) facilities. Since detailed failure data are not available for this barrier, $C(t)$ is estimated following the expert-based procedure. The results are compared with those obtained assuming that the performance of DI is not impaired by aging, to show the usefulness of the proposed KPI definition.
The remainder of the paper is as follows: Section 2 presents the novel KPI definition, Section 3 shows the

application to the case study; in Section 4, conclusions are drawn.

2. Novel KPI definition

The new KPI formulation is justified by acknowledging that safety barriers performance degrades with aging. A corrective factor $C(t)$, that accounts for the actual (at time t) performance of the barriers is, thus, used to modify the no-aging basis KPI (KPI_0) as follows:

$$KPI_{new}(t) = KPI_0 \cdot C(t) \tag{1}$$

Such corrective factor is expected to catch the typical phases that aging systems pass through during their lifetime (Jiang et al., 2003):

- "Infant mortality", during which failures caused by defects in production and/or damage in the shipment or assembly occur with a decreasing failure rate.
- "Useful life", during which random failures occur with a constant failure rate.
- "Wear out", during which the failure rate is increasing due to the aging of the system.

To do this:

- when sufficient barrier failure data are available, a Q-Weibull model (Assis et al., 2013) can be used;
- when barrier failure data are scarce, which is often the case in practice, an expert-based Weibull-like distribution can be used to anchor the different stages of the barrier life with the few, limited data available.

2.1 Q-Weibull model

The Q-Weibull distribution model (Picoli et al., 2003) is a generalized formulation of the Weibull distribution model that can accommodate a large variety of assumptions on the hazard rate (e.g., unimodal, bathtub-shaped, monotonic and constant) (Xu et al., 2017).
The Probability Density Function (PDF) of a Q-Weibull distribution $f_q(t)$ of Eq. (16) can, indeed, be obtained from the PDF of a Weibull distribution $f_w(t)$ of Eq. (17) by substituting the exponential function with a Q-exponential exp_q of Eq. (18) (Assis et al. 2013):

$$f_q(t) = (2-q)\frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} exp_q\left[-\left(\frac{t}{\eta}\right)^{\beta}\right], \quad with\ q < 2 \tag{1}$$

$$f_w(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \tag{2}$$

$$\exp_q = \begin{cases} (1+(1-q)\cdot x)^{\frac{1}{1-q}}, if\ (1+(1-q)\cdot x) \geq 0 \\ 0, \quad otherwise \end{cases} \tag{3}$$

where β and q are shape parameters, η is the scale parameter, and $q < 2$ is necessary for the normalization requirement. Vice versa, the Q-Weibull is reduced to the Weibull when $q \to 1$.
The hazard rates $h_w(t)$ and $h_q(t)$, for the Weibull and the Q-Weibull distribution, respectively, are the following:

$$h_w(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \tag{4}$$

$$h_q(t) = \frac{\frac{(2-q)\beta}{\eta^{\beta}} t^{\beta-1}}{1-(1-q)\left(\frac{t}{\eta}\right)^{\beta}} \tag{5}$$

Q-Weibull distributions are, thus, suitable to model also the bathtub-shaped hazard rate typical of an aging system.
To estimate the Q-Weibull parameters (i.e., q, β and η), a Maximum Likelihood (ML) approach can be used (Genschel & Meeker, 2010). Due to the strong nonlinearities, a numerical approach can be adopted to solve the ML problem (Xu et al., 2017), such as, in this work, the Non-dominated Sorting Genetic Algorithm (NSGA-II) (Deb et al., 2002).
To do this, the ML problem has to be reformulated as a constrained optimization problem.
Let $\boldsymbol{t_f} = (t_{f_1}, t_{f_2}, \dots, t_{f_O})$ be a vector of observed failure times $t_{f_1}, t_{f_2}, \dots, t_{f_O}$, independently drawn from a Q-Weibull distribution. The likelihood function is given by (Xu et al., 2017):

$$L(\boldsymbol{t_f}|\eta,\beta,q) = \prod_{o=1}^{O} f_q(t_{f_o}) \tag{6}$$

The log-likelihood function can then be written as follows:

$$\begin{aligned} L_{log}(\boldsymbol{t_f}|\eta,\beta,q) = {} & Oln(2-q) + Oln(\beta) \\ & - O\beta\ln(\eta) \\ & + (\beta-1)\sum_{o=1}^{O}\ln(t_{f_o}) \\ & + \frac{1}{1-q}\sum_{o=1}^{O}\ln\left[1 - (1-q)\left(\frac{t_{f_o}}{\eta}\right)^{\beta}\right] \end{aligned} \tag{7}$$

Then, the constrained optimization problem is:

$$(\eta,\beta,q) = argmax\left(L_{log}(\boldsymbol{t_f}|\eta,\beta,q)\right) \tag{8}$$

subject to

$$2-q > 0 \tag{9}$$

$$1-(1-q)\left(\frac{t_{f_o}}{\eta}\right)^{\beta}>0, i=1,\dots,n \quad (10)$$

$$\eta > 0 \quad (11)$$

$$\beta > 0 \quad (12)$$

The results of the optimization problem are the parameters (η, β, q) that define the Q-Weibull distribution that best represents the failure data $\boldsymbol{t_f}$. If no preventive maintenance is performed on the system, the corrective factor $C(t)$ is straightforwardly defined as follows:

$$C(t) = 1 - h_q(t) \quad (13)$$

where $h_q(t)$ is the hazard rate for the obtained Q-Weibull distribution. Such corrective factor is large in the useful life phase and small in the infant mortality and wear out phases, which are characterized by a larger failure rate. In **Fig. 1**, an example of $C(t)$ is shown.

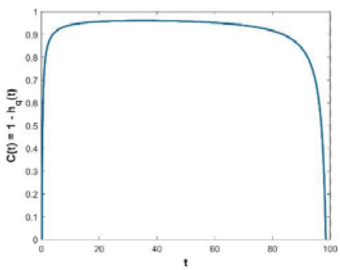

Figure 1: Example of $C(t)$ ($q = -1, \beta = 0.1, \eta = 102400$).

If, on the other hand, preventive maintenance is performed on the system, $h_q(t)$ can be modified as follows (Wang et al., 2000):

$$h_{q,m}(t) = \begin{cases} h_q(t) \text{ } if \text{ } t \le t_1 \\ h_q(t)\left(1-\delta e^{-\alpha s(t)}\right) \text{ } if \text{ } t > t_1 \end{cases} \quad (14)$$

where δ is the influence of preventive maintenance (if $\delta = 0$ the maintenance is ineffective and if $\delta = 1$ the maintenance is perfect), α is the rate at which the influence of preventive maintenance decreases with time, $s(t)$ is the operating time since the last maintenance intervention and t_1 is the end time of the infant mortality phase (in which no preventive maintenance is carried out). The corrective factor $C(t)$ is then defined as follows:

$$C(t) = 1 - h_{q,m}(t) \quad (15)$$

In **Fig. 2**, an example of $C(t)$ in case of preventive maintenance performed once every two years is shown.

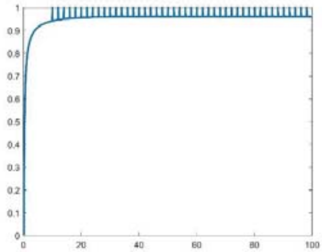

Figure 2: Example $C(t)$ in case of preventive maintenance ($q = -1, \beta = 0.1, \eta = 1024000^{-4}$, $\delta = 1$, $\alpha = 0.1$).

2.2 Expert-based model

In case of scarcity of barriers failure data, which is often the case in practice, $C(t)$ can be estimated using a Weibull-like distribution anchored on expert-defined anchor points. A piecewise defined Weibull distribution, where $f_{w_1}, f_{w_2}, f_{w_3}$ are the functions defining each phase, is estimated using the following expert-based anchor points:

- Time t_1, which is the end time of the "infant mortality".
- Hazard rate h_{w_2}, which is the hazard rate of the "useful life".
- Time t_3, which is the time of beginning of the "wear out".

Therefore, in case of no preventive maintenance, the expert-defined corrective factor $C(t)$ is as follows:

$$C(t) = \begin{cases} 1 - h_{w_1}(t), & if \ t \le t_1 \\ 1 - h_{w_2}, & if \ t_1 < t < t_3 \\ 1 - h_{w_3}(t), & if \ t \ge t_3 \end{cases} \quad (16)$$

where h_{w_1}, h_{w_2} and h_{w_3} are, respectively, the hazard rates derived from f_{w_1}, f_{w_2} and f_{w_3}. To assure the continuity of the piecewise Weibull distribution, the following conditions (Eqs. (17-18)) must be met:

$$\lim_{t \to t_1^-} C(t) = \lim_{t \to t_1^+} C(t) = C(t_1) \quad (17)$$

$$\lim_{t \to t_3^-} C(t) = \lim_{t \to t_3^+} C(t) = C(t_3) \quad (18)$$

Since the parameters β_1 and β_3 are not uniquely determined with the anchor points and the conditions of Eqs. (17-18), they need to be tailored to the specific case study, to best fit the slope of the hazard rate in the infant mortality and wear out phases.

In **Fig. 3**, an example of an expert-defined $C(t)$ is shown.

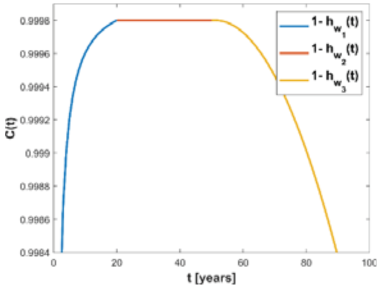

Figure 3: Example of expert-defined $C(t)$ ($t_1 = 20\ y$, $h_{w_2} = 2 \cdot 10^{-4}, t_3 = 50\ y$).

If preventive maintenance is performed on the system, $C(t)$ can be instead defined as follows (Wang et al., 2000):

$$C(t) = \begin{cases} 1 - h_{w_1}(t)\ if\ t \leq t_1 \\ 1 - h_{w_2}(t)\left(1 - \delta e^{-\alpha s(t)}\right)\ if\ t > t_1 \end{cases} \quad (19)$$

The useful life phase may continue until the end of the design life of the system, since the system is assumed to never enter the wear out phase if perfect preventive maintenance is regularly performed. In **Fig. 4**, an example of an expert-defined $C(t)$ is case of perfect preventive maintenance, performed once every two years, is shown.

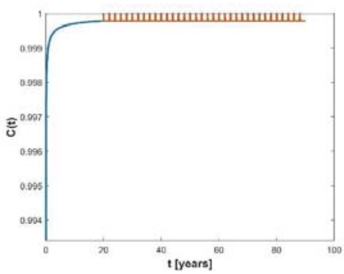

Figure 4: Example of expert-defined $C(t)$ in case of preventive maintenance ($t_1 = 20\ y$, $h_{w_2} = 2 \cdot 10^{-4}$, $\delta = 1$, $\alpha = 0.1$).

3. Case study

The methodology presented for the accounting for aging when calculating the KPI of safety barriers has been applied on an O&G preventive safety barrier, called Design Integrity (DI), whose function is to ensure that functional performance standards are met, through the redesign of the asset or the definition of specific mitigation requirements during operation, maintenance, inspection and control. The available data comes from a typical O&G asset. DI is an event-based safety barrier, whose events (e.g., number of incidents, alarm counts, number of Emergency Shutdowns (ESDs) or Process Shutdown (PSDs)) are customary counted for calculating event-based KPIs that are compared with reference KPI distributions preliminary defined; these KPIs are, finally, aggregated for the evaluation of the probability of DI to be in Health State (HS) "High", "Medium" or "Low" (H, M, L, respectively) (Di Maio et al. 2021). To model the relationship between KPIs and HS {H,M,L} we resort to a probabilistic relationship, where prototypical conditions are used as anchor points, as in (Di Maio et al. 2021).

3.1 Current KPI definition

The current DI KPI consists in the aggregation of two KPIs:

1. KPI_1, referred to the events "Rate of opened inhibits/overrides on SECEs", to be compared with a normal distribution N(62,48).
1. KPI_2, referred to the events "Corrective vs total maintenance", to be compared with a normal distribution N(31,13).

These KPIs are aggregated to calculate the probabilities of DI to be in HS {H,M,L} ($P_B(H), P_B(M), P_B(L)$, respectively) as follows:

$$P_B(H) = \frac{P_B(H|KPI_1)W(KPI_1) + P_B(H|KPI_2)W(KPI_2)}{W(KPI_1) + W(KPI_2)}$$

$$P_B(M) = \frac{P_B(M|KPI_1)W(KPI_1) + P_B(M|KPI_2)W(KPI_2)}{W(KPI_1) + W(KPI_2)}$$

$$P_B(L) = \frac{P_B(L|KPI_1)W(KPI_1) + P_B(L|KPI_2)W(KPI_2)}{W(KPI_1) + W(KPI_2)}$$

where

$$W(KPI_j) = exp\left(\frac{KPI_j - \tau}{\tau}\right) \quad (20)$$

and τ is the KPI_j, *j=1,2,* taken at the end of the previous monitoring/inspection interval.

3.2 New KPI definition

Since detailed failure data were not available, the corrective factor $C(t)$ has been estimated with the expert-based procedure of Section 3.2.2, using the following expert-defined anchor points:

- $t_1 = 10\ y$
- $h_{w_2} = 0.2$
- $t_3 = 30\ y$

The parameters of the resulting Weibull distributions, tailored to represent the aging of the considered asset, are the following:

1. $\beta_1 = 0.5, \eta_1 = 0.625$
2. $\beta_2 = 1, \eta_2 = 0.2$
3. $\beta_3 = 3, \eta_3 = 23.81$

The corrective factor $C(t)$ that results from the combination of the three Weibull distributions is reported in **Fig. 5**, in case of no preventive maintenance.

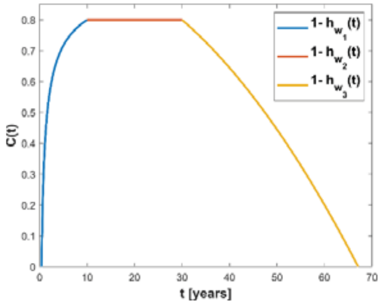

Figure 5: Results of $C(t)$ for the case study.

From the results of **Fig. 5** it is possible to notice that the infant mortality phase presents a steep slope, whereas the wear out phase presents a much gentler slope. This is due to the fact that the production defects and early damages, typical of the infant mortality phase, should be identified (or should lead to failure) in the first months of operation, whereas the aging of the considered asset is a slow process, since the asset is characterized by a long design life.

The corrective factor $C(t)$ in case of perfect preventive maintenance ($\delta = 1$ and $\alpha = 0.1$) performed once every two years is shown in **Fig. 6**.

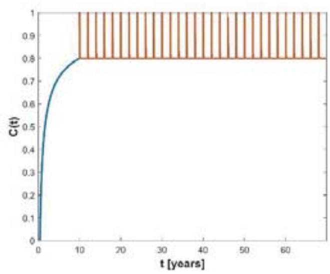

Figure 6: Results of $C(t)$ for the case study in case of preventive maintenance.

From a practical point of view, assuming that the asset whose KPI has to be quantified has an age equal to $t_{age} = 1\,y$, from **Fig. 6** we can calculate $C(t_{age}) = 0.37$ (if we deem that preventive maintenance practice is a realistic assumption); this modifies the no-aging KPIs ($KPI_1 = 0.02$ and $KPI_2 = 0.61$), to $KPI_{1,new} = 7.4 \cdot 10^{-3}$ and $KPI_{2,new} = 0.23$. The aggregation procedure of Section 3.1 can be used to obtain the probabilities of DI to be in HS {H,M,L}, considering $W(KPI_1) = W(KPI_2) = \frac{1}{2}$, since the data of KPI_1 and KPI_2 refer to the first monitoring interval:

- $P_{B,new}(H) = 0.01$
- $P_{B,new}(M) = 0.251$
- $P_{B,new}(L) = 0.739$

to be compared with the no-aging probabilities ($P_B(H) = 0.18$, $P_B(M) = 0.42$, $P_B(L) = 0.40$). The newly defined KPI leads to smaller probabilities for HS High and Medium and to a larger probability of HS Low, reflecting the age of the system that is still in the infant mortality phase and is, thus, exposed to early failures. Such probabilities can be used in a condition-informed risk assessment that takes into account the asset age and adjusts its risk profile accordingly.

4. Conclusions

In this paper, a novel KPI definition is proposed to account for the impact of the aging of safety barriers on their performance. A corrective factor is defined to multiply the non-aging basis KPI value and is quantified with a Q-Weibull model, under abundance of failure data, or with an expert-based Weibull-like distribution, when failure data is scarce. The new KPI formulation has been tested on the DI safety barrier, typically employed in upstream O&G facilities. The proposed approach can quickly assess the performance of aging safety barriers, as shown by the comparison between the non-aging HS probabilities and those obtained with the new KPI, and can enable a condition-informed risk assessment that updates the risk profile as the system ages. Further developments and refinement of the model proposed can focus on additional info derived from DI safety barriers condition monitoring data, the safety margins taken in the design phase, and the facilities process production (pressure, temperature and fluid characteristics) parameters.

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