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A framework for corrosion assessment in metallic structures, from data analysis to risk based inspection

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Highlights

- A stepwise guideline for fully automation quantitative corrosion estimation.
- Enhanced corrosion analysis method by the statistical approach.
- Software tools developed by TWI Ltd implementing the proposed framework.
- A model widely adaptive to various metallic structure suffering from corrosion damage.

Abstract

Metallic corrosion is a big challenge affecting many sectors in a nation's economy. Necessary corrosion prevention actions have to be taken in order to maintain the integrity of engineering assets susceptible to corrosion. This paper proposes a holistic framework to support the management of corrosion in metallic structures. It is a fully automation corrosion assessment process, with risk updated by Bayesian theory. Through analyzing the thickness data measured by non-destructive testing (NDT) techniques, the influence of corrosion on the component can be estimated using statistical methods, which will enable users to make decisions on maintenance based on quantitative information. A case study using corrosion data from a steel bridge is included to demonstrate the proposed framework. It improved the conventional corrosion analysis method by the proposed statistical approach using representative thickness data, which aims to take full use of the remaining life. This model can be adapted to a wide range of metallic structure suffering from corrosion damage.

Keywords

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corrosion estimation; steel bridge; metallic structure; risk based inspection; software.

Nomenclature

A	Surface area of the object	2D ACF	Two-dimensional auto-correlation function
Age	Service time, year	CDF	Cumulated density function
CR	Corrosion rate	COF	Consequence of Failure
CI	Confidence interval, %	EVD	Extreme value distributions
p	Probability of the quantile p of a statistical distribution	EVT	Extreme value theory
S	Small specimens that are sampled randomly from this object	FFS	Fitness for Service
time	Failure time, independent variables	GEVD	Generalized Extreme Value distribution
t_{min}	Minimum measured thickness	iid	Independent and identically distributed
t_{nom}	Nominal thickness	MLE	Maximum likelihood estimation
T	Return period	MRL	Mean residual life
x	Random variable from the statistical distribution	MRR	Median rank regression
X_p	GEVD return level	ξ	Shape parameter of a EVD
μ	Mean of a statistical distribution / population	MCMC	Markov chain Monte Carlo
$\bar{\mu}$	Location parameter of an EVD	NACE	National Association of Corrosion Engineers
σ	Standard deviation of a statistical distribution	POT	Peak-over-Threshold
$\bar{\sigma}$	Scale parameter of a EVD	POF	Probability of Failure
RUL	Remaining useful life	RBI	Risk based inspection

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1. Introduction

Steel bridges play an important role in the transportation network and support the nation's economy and traffic [31]. Corrosion is one of the main causes of deterioration of steel bridges [32]. It may cause metal loss and fatigue cracks in the steel components, which would lead to the collapse of steel bridges [32]. Therefore, periodical inspection of steel bridge is essential for the long-term safety of public infrastructures.

A traditional method of inspecting a steel bridge is to send inspectors up to the bridge using scaffolding or ropes, and inspect it manually [31]. The disadvantages of this method are the inconvenient and dangerous for the inspectors, as well as the quality of the inspection, which can be subjective as it mainly depends on the inspectors' experience. Another traditional way is to lift inspectors and some measuring equipment to the bridge using a bucket truck or platform snooper [31]. Although is better than using scaffolding or ropes, there are still disadvantages exist on the safety of inspectors, and sometimes, the road may be too narrow or even be blocked, so that the inspection truck may not be able to reach to bridge.

To overcome these disadvantages, inspection robots are built, assisting inspectors to reach bridges, which are too dangerous to be accessed by a human due to high altitudes, radiation and other hazardous environments. Generally, there are two types of inspection robots, namely climbing robots [20] and aerial robots [30]. Compared with climbing robot, an aerial robot can achieve a high level of complexity for professional applications and speed with a low cost [31].

In terms of steel bridge corrosion detection, many state-of-the-art techniques were introduced, such as infrared thermography [9], giant magnetoresistance [32], computer-vision based method [16], Ultrasonic testing method [19], etc. Among these methods, the Ultrasonic testing method attracted our attention, because after processing, the thickness data, which is a widely recognized way for corrosion analysis in industry [4], can be obtained from the Ultrasonic testing (UT) data.

The paper is based on an Innovate UK (IUK) funded project – AS-SAI, using thickness data from the UT sensor installed on an aerial robot (namely, an unmanned aerial system) to carry out corrosion estimation for steel bridges. It is a fully automation corrosion assessment process, sending aerial robot to the target steel bridge, data acquisition from UT sensor, converting UT data to thickness data, and corrosion assessment. The paper focused on using the thickness data to automatically carry out quantitative corrosion estimation. The contribution includes: 1) The development of a stepwise guideline for quantitative corrosion estimation, using statistical methods for use in a framework developed for integrity assessments of structures that are susceptible to corrosion damage. 2) The conventional corrosion analysis, which estimated corrosion rate through minimum thickness data, was improved by our proposed statistical approach. 3) A case study is included to demonstrate the application of this model to support the integrity assessment of a metallic component using the corrosion data obtained from a steel bridge. A suite of software tools has been developed by TWI Ltd to perform the corrosion assessment, as an outcome from this research. In addition, the proposed model is envisaged to be adaptive to a wide range of metallic structure suffering from corrosion damage.

2. Background

NACE (National Association of Corrosion Engineers) International recommend that corrosion assessment can be conducted following the below procedures (derived from NACE Internal Corrosion Direct Assessment Methodology [18]), which is the traditional procedure that is followed by corrosion engineers:

- Step 1: Pre-assessment – conducting a detailed right-of-way (ROW) inspection and collecting all operating data
- Step 2: Indirect inspection – identifying factors affecting corrosion distribution

- Step 3: Direct examination - performing excavations and conducting detailed examinations to determine whether corrosion has occurred
- Step 4: Post Assessment - analyzing the data collected from the three previous steps to provide test results and recommendations necessary for corrosion protection

Nowadays, the abovementioned traditional procedure has been further developed to incorporate models from different disciplines (such as statistics) to improve its flexibility and capability. Application of statistical methods, as proposed in this paper, increases the efficiency of the Step 1 and Step 2 in identifying corrosion distribution as well as data collection, processing and management. It can also provide recommendations on corrosion management strategy, such as future inspection intervals, hotspots identification, corrosion rate estimation, etc., as part of the Step 4 outputs. This section reviews various existing models [22, 23, 25, 28, 29] that use statistical methods for corrosion assessment.

Studies on the statistical nature of corrosion and its relationship to inspection have been carried out since 1950s. The initial work using extreme values to simulate corrosion was carried out by Gumbel to estimate the condition of the pipeline with external corrosion [29]. Especially in Japan, the use of these methods for analyzing corrosion data has been referred to consistently since 1980s. A useful overall text to the statistical method of analyzing corrosion data was given by Kowaka [14]. However, such work does not comprehensively include strategies of data collection by NDT (non-destructive testing) methods, and does not generally validate the results obtained by comparing a sample with the whole population.

To address this, a guideline was prepared by TWI Ltd for the Health and Safety Executive (HSE) in 2002 to advice plant engineers and inspection personnel on methods for analyzing and extrapolating inspections for large plant items [29]. It introduced methods of statistical analysis of corrosion inspection data, including general comments on data collection with suggestions of data analysis methods using normal distribution and extreme value distribution families. At the time when [29] was published, complete data population sets rarely occurred in practice, and full scanning of a component was considered impractical. Therefore, the target of statistical treatment and procedures was to make a prediction on the basis of a limited sample information to infer the greater population behavior. The supporting theory is the belief that a statistical sample may follow the same distribution of its parent population and this may be a fundamental distribution. This can be further demonstrated using an example given by Kowaka [14] – in which laboratory SCC acceleration tests were used to predict the condition in field service. However, the difference of coupon size and duration between laboratory test and the field examination was extremely large, making any direct extrapolation of laboratory data for life prediction unreliable.

Nowadays, with the development of non-destructive testing technology, high resolution, and complete inspection coverage of the component surface for the corrosion inspection is becoming more common. This means the corrosion measurement from inspection will show the entire condition of the component surface in a large size sample. Therefore, the conventional way of data analysis needed updating to keep up with the development of inspection technology. A method for bridging such technology gap was developed by Shibata [25] based on statistical theory of extreme values. To apply this method, Shibata [25] proposed a concept of “size factor (T)”, which is the return period of the sample data following a generalized extreme value distribution (GEVD). This method forms the basis of the framework proposed in this paper. In addition, considering the GEVD may not always be the best-fitting probability distribution model for measured thickness data, in this paper, we add a procedure to select a best-fitting probability distribution model among some candidate distributions mentioned in [24].

As a holistic model, in addition to data processing, the proposed framework includes steps to conduct integrity assessment following corrosion assessment. This includes the estimation of minimum thickness for FFS assessment, corrosion rate for remaining life prediction and the plot of probability of failure (POF) for RBI. Reference [27] provided POF calculation method using statistical data. In this paper, same method is applied to calculate the probability of failure caused by corrosion using thickness data. Reference [10] gave equations for corrosion propagation for rebar in concrete structure. In this paper, to better estimate the corrosion propagation for the target bridges, regression method is applied when user have historical data. According to API 579/ASME FFS-1 [4], if the remaining thickness is less than the design minimum required thickness, the component is not fit for continuous service. Since corrosion is a time dependent damage mechanism, it is important to predict when the component will fail as well as its failure probability even if it was serviceable at the time of inspection. A limit state equation was proposed in [23], and applied in analyzing corrosion of a pipeline after 20 years in operation. In which case, failure was defined as that leakage would happen when the remaining thickness becomes zero. These models will also be included in this paper as part of the assessment framework. As part of the holistic model, the Bayesian approach, which has a powerful capability of probability reasoning, dynamic behavior modeling and multi-model synthesis [17], is applied for POF updates after inspection carried out. The model is developed upon the assumption that higher inspection effectiveness levels will reduce the uncertainty of the damage state of the component hence improving the accuracy of the assessment.

Although various analysis methods have been developed and guidelines have been proposed to apply these methods routinely, this paper seeks to provide step-wise analysis procedures in a single document. The software developed implementing this framework will help the non-specialists in statistics to perform data collection, analysis and extrapolation.

3. Framework flowchart

Figure 1 is the flow chart of the overall approach from data collection and processing to risk prediction and inspection scheduling, including function to update the results after receiving additional data. The following paragraphs will explain each step in detail. In the flowchart, the text box filled with green color are the input parameters, which mainly include:

- Thickness data (including both historical and new thickness readings);
- Minimum required thickness (or design thickness and corrosion allowance);
- Inspection specification;
- Service age;
- Consequence of failure (COF).

The text box filled with pink color is the expected output from this assessment, including:

- The best fit of the distribution that the thickness measurement follows;
- Representative thickness of the current data;
- Corrosion rate;
- Predicted remaining useful life (RUL);
- Risk value and a risk matrix.

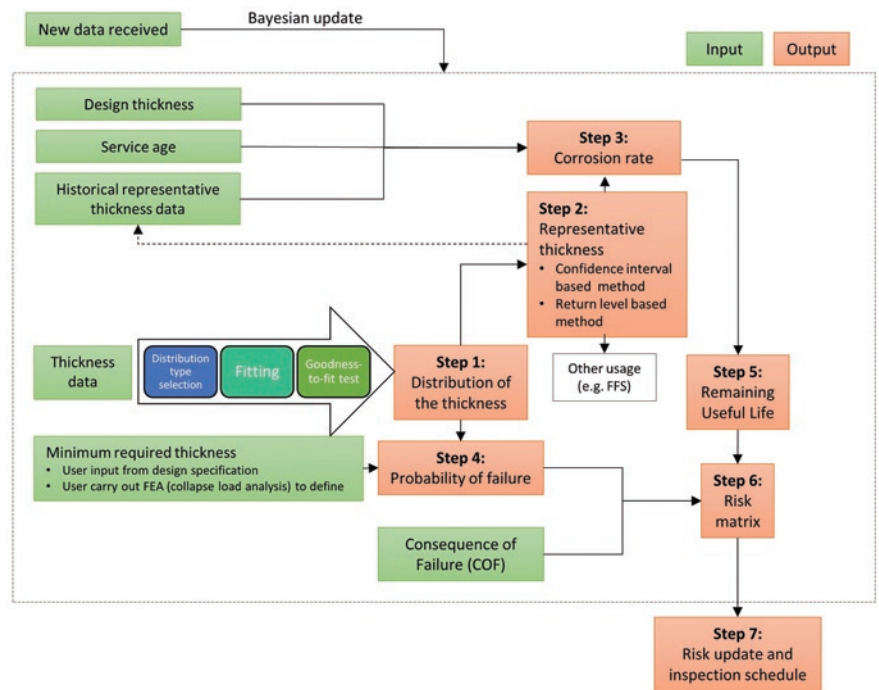


Fig. 1. Flow chart for the overall approach

3.1. Step 1: Fit a distribution

Statistical corrosion assessment is supported by the belief that a statistical sample may follow the same distribution of its parent population and this may be a fundamental distribution [14, 29]. It means analysing the thickness measurements from a local area to extrapolate the condition of the entire component. Accordingly, the first step after receiving the thickness data is to characterise it by a distribution.

This process starts from identifying the candidate distributions. However, the choices of the statistical distributions seem endless, but the options can be narrowed by identifying the following properties:

- Is the data discrete or continuous?
- What is the Skewness and Kurtosis of the data set?
- How is the likelihood of observing extreme values in the distribution?

By identifying the above properties, it becomes easier to choose the statistical distribution for a given dataset. A simplified procedure for checking appropriate types of distribution taking into account of these criteria is shown in Figure 2 adapting information from [8]. According to [25], the distributions commonly used for corrosion data includes normal, lognormal, Poisson, Spatial and three types of extreme value distributions (Type I, II, III as shown in Figure 3).

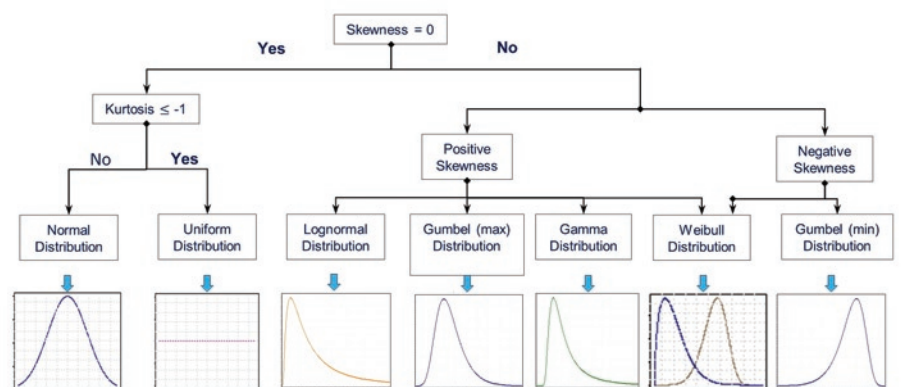


Fig. 2. Simplified distributional choices

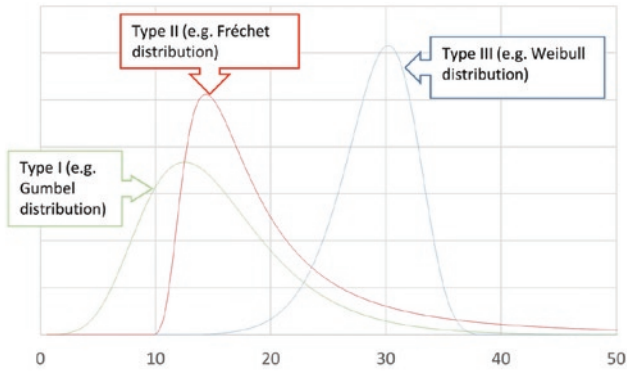


Fig. 3. Typical example PDF of Type I, II, III distributions of GEVD

The parameters of the distributions can be estimated using various methods such maximum likelihood estimation (MLE), method of moments, maximum spacing estimation or median rank regression, etc., depending on the target distribution. Finally, the goodness-of-fit test should be performed to quantify how the selected distribution matches the original thickness data. There are numerous statistics measurements and statistical fitting tests, which are commonly used for evaluating the goodness of the distribution fitting. Some of the popular statistics measurements are R squared and root mean square error, and statistical fitting tests include Kolmogorov-Smirnov test, Anderson-Darling test, Cramer-von Mises test, Chi-Squared test, etc.

3.2. Step 2: Calculation of representative thickness

Traditionally, the minimum measured thickness from the inspection is used to estimate the corrosion rate, perform FFS assessment and predict RUL of the component. However, using the lowest value as minimum measured thickness is overly conservative for many applications. Instead, it is proposed in this model to choose a representative value of given thickness data for the assessment, called “representative thickness (t_r)”.

Depending on the nature of the data, there are three commonly employed analysis methods:

Method A: Identify a fit to the underlying distribution (parent distribution) of the raw data.

Method B: Partition the surface into rectangular “blocks”, and fit an extreme value distribution to the minimum thickness/ maximum wall loss of these blocks.

Method C: The peak-over-threshold method by fitting a Generalised Pareto distribution (GPD) to the exceedances.

Method A is usually the first choice and the classical method to evaluate corrosion by extrapolation based on confidence index of statistical distribution that is symmetric such as Normal, Logistic, Cauchy, Uniform distributions, etc. However, in fact, the true parent distribution from inspection sample data is hard to identify. Moreover, the confidence index approach may not applicable to the asymmetric distributions that may depict reality more closely. Method B, using extreme value theory, is a good alternative, especially for localised corrosion, to model the extremely corroded area of equipment and components. In cases when the corrosion does not happen uniformly or block minima/maxima cannot be extracted, such as tank bottom wall loss (pit depth), Method C based on GPD is more appropriate. Method C is outside the remit of this paper as the underlying data is not of the type to which it is suited.

The flow chart of calculating the representative thickness is shown in Figure 4. For Method A, the confidence interval (CI) is a user input based on engineering judgement. The procedure of applying Method B is as follows:

Taking the example of minimum generalised extreme value (GEV (min)) distribution, its CDF is written as:

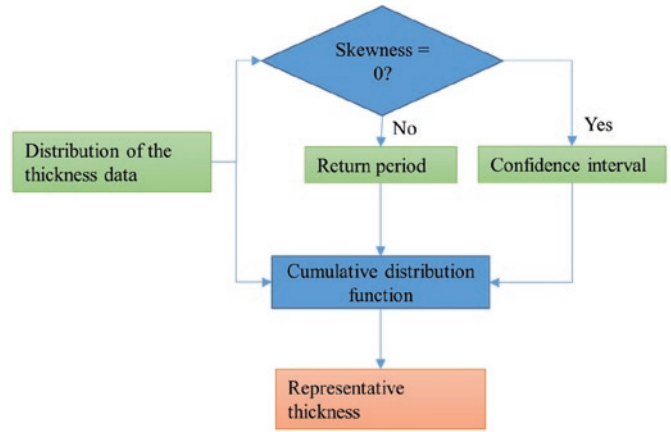


Fig. 4. Flow chart of representative thickness calculation

$$F(x; \mu, \sigma, \xi) = \begin{cases} 1 - \exp \left\{ - \left[1 + \xi \left(\frac{-x + \mu}{\sigma} \right) \right]^{-\frac{1}{\xi}} \right\}, \xi \neq 0 \\ 1 - \exp \left[- \exp \left(\frac{x - \mu}{\sigma} \right) \right], \xi = 0 \end{cases} \quad (1)$$

where the ξ , μ , and σ represent a shape, location, and scale of the distribution function, respectively. $\sigma \geq 0$, and $1 + \xi \left(\frac{x - \mu}{\sigma} \right) \geq 0$. In extreme value terminology, quantities such as t_r is normally named as return level. In GEVD, the return level is defined as a level that is expected to be equal or exceeded on average once every certain observations/ interval (T) with a probability of p [7], T is called return period and:

$$p = \frac{1}{T} \quad (2)$$

The return level X_p hence can be calculated using quantile function as:

$$X_p = \begin{cases} \bar{\mu} + \frac{\bar{\sigma}}{\xi} \left\{ 1 - [-\ln(1-p)]^{-\xi} \right\}, \xi \neq 0 \\ \bar{\mu} + \bar{\sigma} \cdot \ln[-\ln(1-p)], \xi = 0 \end{cases} \quad (3)$$

To apply this method, analyser needs to identify the return period first. To do so, Shibata [6]. proposed a method called “size factor”, where the return period T is calculated as:

$$T = \frac{A}{S} \quad (4)$$

As illustrated in Figure 5, A is the surface area of the object, i.e. the total area of inspection and S is the small specimen that is sampled randomly from this object. Apply size factor to Equation (1) to (3), the representative thickness can be calculated. In this process, the calculated return level t_r represents the maximum corrosion at a given return period, T. In the other word, it estimates the maximum corrosion for the larger surface area (A), which is T times larger than the small sample area (S). Choice of block size S is scenario based and critical. If it is too small, the limiting arguments supporting the GEV might not be valid, and the extrema will be too close to assume iid (independent and identically distributed), while if it is too large, there will be insuf-

efficient data for analysis and result in sampling errors. One possible approach in this scenario is to define the block size by looking at the correlation among data. It is to be noted that Extreme Value Theory (EVT) is based on the assumption that individual thickness measurements are iid variables that any correlation between the data is negligible. Stronger correlation between adjacent data points is described in [21] as “clustering” and such high degree of correlation would overthrow the basic assumption of EVT and make it difficult to extrapolate the underlying distribution of raw data, even if Method A had revealed an adequate fit [23]. Reducing the sample to that of the block extrema can help to mitigate such clustering effect. Therefore, in principle, the chosen dimension (or area) of the block should enable the pairs of data points separated by such dimension (or area) to be weakly correlated. In other words, to reduce clustering effect, the chosen dimension of the block should enable sampled data points to be weakly correlated. For instance, the approach used by [23] to gauge the strength of correlation is through computing the “two-dimensional auto-correlation function (2D ACF)” by applying a pair of Fast Fourier transforms.

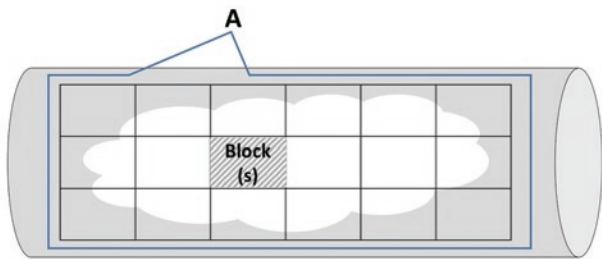


Fig. 5. Example of inspection surface

3.3. Step 3: Corrosion rate calculation

Corrosion rate is the speed at which any metal in a specific environment deteriorates. It can also be defined as the loss per year in thickness of a metal component due to corrosion. The corrosion rate depends on the environmental conditions and the properties of the material [15]. The corrosion rate can be obtained by carrying out laboratory tests, historical data analysis or calculation using the formulas from codes and guidelines. In terms of data driven approach, depending on the availability of the data, there are two methods:

Method 1: When the historical data is not available, the corrosion rate can be calculated by Equation (5).

$$CR = \frac{t_r - t_{nom}}{Age} \quad (5)$$

where t_r is the current representative thickness, t_{nom} is the design nominal thickness of the component. Age is the time in service so far.

Method 2: If the historical thickness data are available, the corrosion rate can be calculated by fitting all the representative thickness data to a regression equation, such as linear regression and polynomial regression. According to the linear regression method, the corrosion rate CR is an absolute value of the slope of the fitted line. An example of corrosion rate calculation using linear regression model is shown in Figure 6.

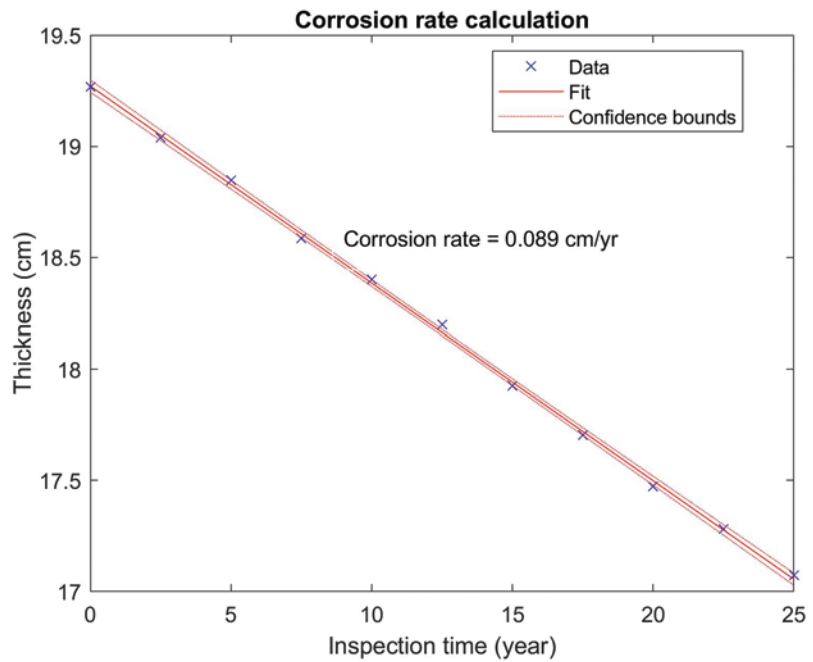


Fig. 6. An example of corrosion rate calculation using linear regression model

3.4. Step 4: Calculation of the probability of failure (POF)

The probability of failure (POF) represents the probability that the component is no longer fit for service. Definition of failure is based on the purpose of assessment. In corrosion assessment, when the thickness degraded to below a certain critical value, the component is considered not serviceable any more, i.e. the component is failed due to corrosion. The critical thickness could be the minimum required thickness (t_{min}) retrieved from an FFS assessment or a value given by engineer such as design nominal thickness deducted by future corrosion allowance. The process of calculating the POF is shown in Figure 7.

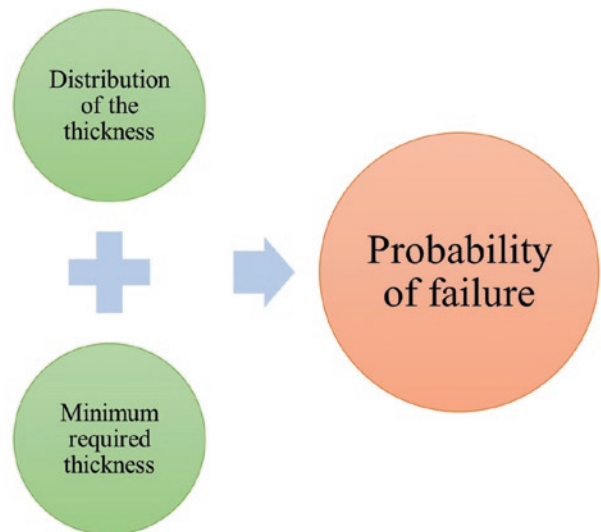


Fig. 7. Flow chart of calculating the POF

The equation of POF at the time of inspection is given by:

$$POF = \int_0^{t_{min}} f(s)ds \quad (6)$$

where $f(s)$ is probability density function (pdf). t_{min} is the minimum required thickness.

While in case if the POF prediction is of interest, the corrosion rate (CR) should be factored in the assessment. According to the above-mentioned failure threshold, a limit state equation (LSE) for corrosion damage can be defined as [5]:

$$z(\text{time}) = (t_m - CR \cdot \text{time}) - t_{min} \quad (7)$$

where t_m is the observed thickness measurements and time is the independent variable. Considering t_m and/or CR are distributed, the future POF then can be defined as:

$$\text{POF} = P[z(\text{time}) \leq 0] \quad (8)$$

To compute the POF from above equations, the Monte Carlo Simulation (MCS) method or First / Second Order Reliability Method (FORM/SORM) are good options.

3.5. Step 5: Prediction of RUL

The remaining useful life (RUL) of an asset is defined as the length from the current time to the end of the useful life [26]. According to its definition, the RUL can be calculated by Equation (9):

$$\text{RUL} = \frac{t_r - t_{min}}{CR} \quad (9)$$

where t_{min} is the minimum required thickness that is obtained in Step 4, t_r is the current representative thickness that is calculated in Step 2 and CR is the corrosion rate that obtained in Step 3.

3.6. Step 6: Show risk assessment and prediction on a risk matrix

In a risk assessment approach, a risk matrix is developed to define the level of risk by considering the category of probability against the category of consequence severity. It increases the visibility of risks and assist management decision making. On the risk matrix, the current risk of the asset system under consideration and the RUL should be presented on the risk matrix to support the end user in inspection scheduling.

In the risk matrix, the consequence of failure (COF) is defined as the potential consequences for the component, personnel, and the environment if the adverse event occurred. In this paper, the COF is assessed using standards proposed in [33], is divided into four categories listed in Table 1; the POF has four categories as well as listed in Table 2.

Table 2 The POF ranking and value

Ranking	POF value
Low	0% - 0.25%
Moderate	0.25% - 0.5%
High	0.5% - 0.75%
Severe	0.75% - 1%

3.7. Step 7: Updated probability using Bayesian theory

Bayesian theory is a probabilistic approach which applies the conditional probability principals to work with uncertainties [11]. In this paper, the Bayesian theory is applied for POF updates when there is additional inspection data. The model is developed upon the assumption that higher inspection effectiveness levels will reduce the uncertainty of the damage state of the component hence improving the accuracy of the assessment. The inspection effectiveness is measured as probability of detection (POD) and false call ratio (FCR).

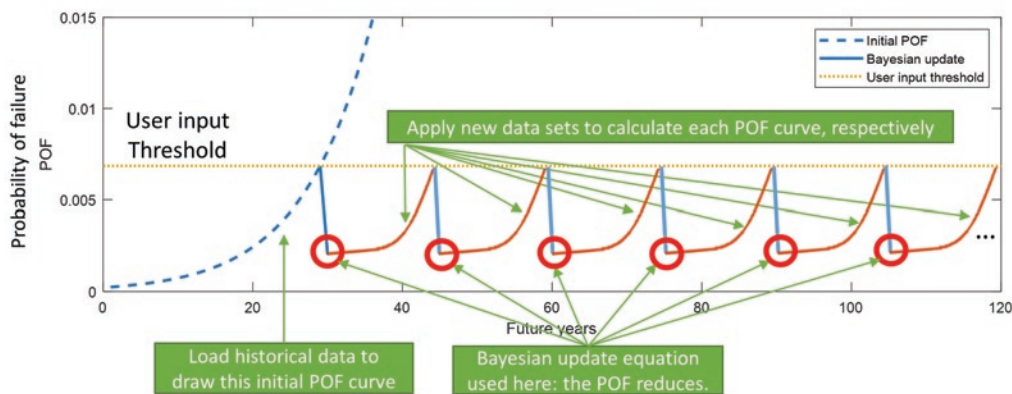


Fig. 8. Probability of failure curve when applied new data and Bayesian theory

Table 1. The COF ranking and value

Ranking	COF value	Description
Low	1	None or very minor effect on safety, health, and environment.
Moderate	2	A moderate effect. The system requires scheduled repair. A failure which may cause moderate injury, moderate property damage, or moderate system damage which will result in delay or loss of system availability or mission degradation. 100% of the mission may need to be reworked or process delayed.
High	3	System performance is degraded. Some safety functions may not operate. A failure causes injury, property damage, or system damage. Some portion of the mission is lost. High delaying restoring function.
Severe	4	The system is inoperable with loss of primary function. Failure can involve hazardous outcomes and/or noncompliance with government regulations or standards.

Table 3. Conditional probability table for driving Equation (10)

	Defect yes (A ⁺)	Defect no (A ⁻)	
UT results, positive (B ⁺)	$P(A^+ \cap B^+) = \text{POF}_{\text{initial}} \times \text{POD}$	$P(A^- \cap B^+) = (1 - \text{POF}_{\text{initial}}) \times \text{FCR}$	$P(A^+ \cap B^+) + P(A^- \cap B^+)$
UT results, negative (B ⁻)	$P(A^+ \cap B^-) = P(B^- A^+) \cdot P(A^+)$ $P(A^+) = \text{POF}_{\text{initial}} \times (1 - \text{POD})$	$P(A^- \cap B^-) = (1 - \text{POF}_{\text{initial}}) \times (1 - \text{FCR})$	$P(A^+ \cap B^-) + P(A^- \cap B^-)$
	$\text{POF}_{\text{initial}}$	$1 - \text{POF}_{\text{initial}}$	1

Figure 8 shows the POF and its updating using Bayesian theory. The initial POF curve is obtained by using historical data, and applying the method described from Step 1 to Step 6. Accordingly, future inspection (or maintenance) is scheduled, which provides new data to update the initial POF. The new datasets provide new POF (POF_{new}) curves corresponding to the data as processed from Step 1 to Step 6 (the orange curves shown in Figure 8).

Note that an updated POF value (POF_{update}) can be calculated using Equation (10) if the effectiveness of inspection is available in terms of POD and FCR. An updated POF value can be obtained for POF_{initial} or POF_{new} although only the former is shown in Equation (10).

$$\text{POF}_{\text{update}} = \frac{\text{POF}_{\text{initial}} \times (1 - \text{POD})}{\text{POF}_{\text{initial}} \times (1 - \text{POD}) + (1 - \text{POF}_{\text{initial}}) \times (1 - \text{FCR})} \quad (10)$$

where POF_{initial} is the POF evaluated from previous inspection; POD is the probability of detection, which is used to describe the capability of an inspection to detect flaws; and FCR is the false call ratio (or called false positive ratio), which means the rate that negative events (i.e. no defects) are wrongly categorized as positive (i.e. defects).

Table 3 shows how Equation (10) was derived following recommendations by API 581 [1]. First, assume the probability of UT results regarding unacceptable corrosion defects showing positive is P(B⁺) and the current probability of a component having such defects is P(A⁺) that is equal to POF_{initial}. Then complete Table 3 accordingly; the updated probability of failure, according to the rule of conditional probability [13], can be calculated using Equation (11) which is equivalent to Equation (10):

$$P(A^+ | B^-) = \frac{P(B^- | A^+) \cdot P(A^+)}{P(B^-)} \quad (11)$$

4. Application of software implementing the framework: a steel bridge case study

Corrosion is a major cause of deterioration in steel bridges [15]. The results of this deterioration can range from progressive weakening of a bridge structure over a long period of time to sudden bridge collapse [15]. Hence, corrosion damage must be carefully appraised and evaluated. In some cases, immediate repair or closure is necessary, while in other cases, the conditions created by corrosion can be

tolerated. In order to mitigate the risk of unexpected collapse of a bridge, key components of a bridge should be identified and inspected periodically. In this case study, we focused on one of the most essential components in bridges – girder. The implementation of the proposed model is presented in this section.

The raw data of a bridge girder was obtained from ultrasonic sensors, and was then transformed to thickness readings. The developed software provided the risk assessment of the structure by performing corrosion assessment using statistical method. One critical input of the software was the thickness readings; the histogram of thickness data is shown in Figure 9.

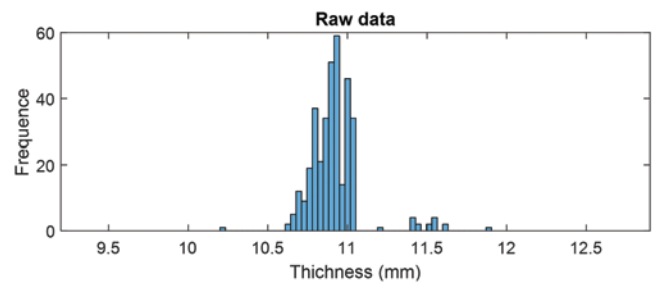


Fig. 9. Histogram of the raw thickness data

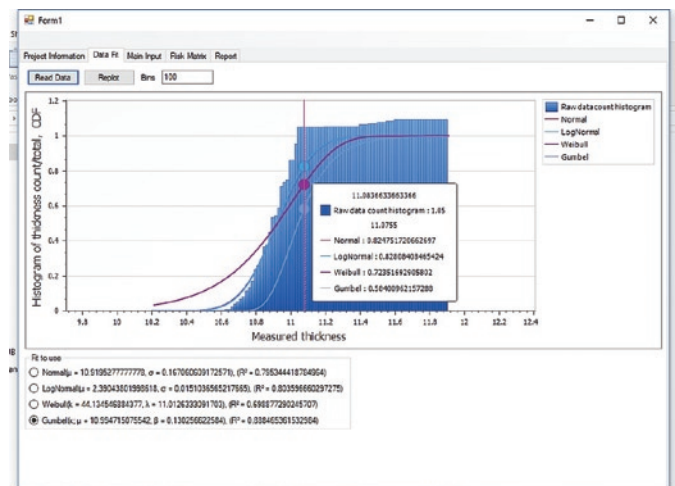


Fig. 10. CDF of real data and fitted distributions

After loading the thickness data into the software, the next step was to select a statistical distribution that best fits to the thickness data. In this case, the candidate distributions include Weibull, Gumbel, Normal and Log-normal distribution. R squared value was applied to

Table 4. R square value of different distributions

Distribution name	Normal	Lognormal	Weibull	Gumbel
parameters	$\mu = 10.9195$	$\mu = 2.3904$	$k = 44.1345$	$\mu = 10.9947$
	$\sigma = 0.1671$	$\sigma = 0.0151$	$\lambda = 11.0126$	$\sigma = 0.1303$
R square value	0.7953	0.8036	0.6989	0.8885

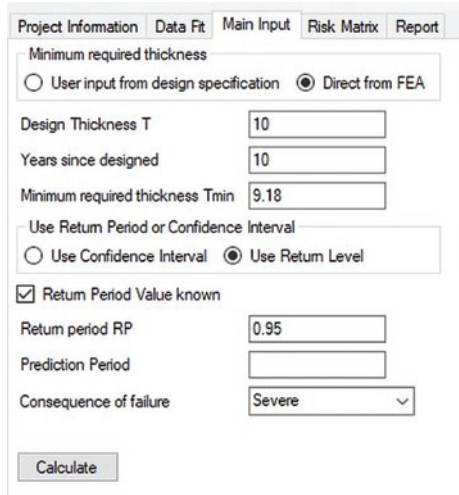


Fig. 11. User input screenshot

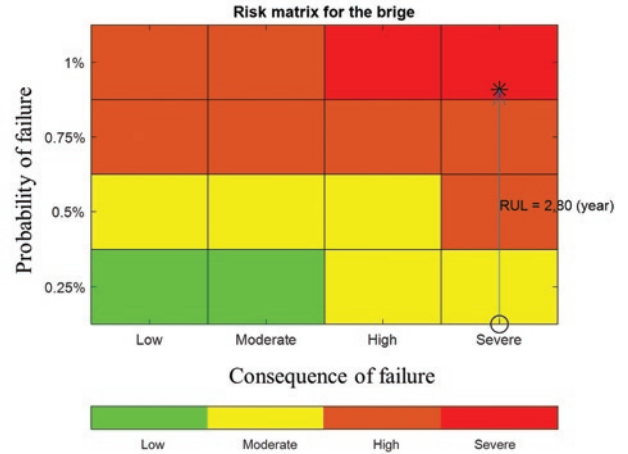


Fig. 13. Risk matrix of the bridge girder

Table 5. The output of the software

Output	POF threshold	Representative thickness (mm)	Current POF	Corrosion rate (mm/yr)	Current remaining useful life (year)
Values	7.8394e-03	10.59	6.3323e-28	0.5	2.8

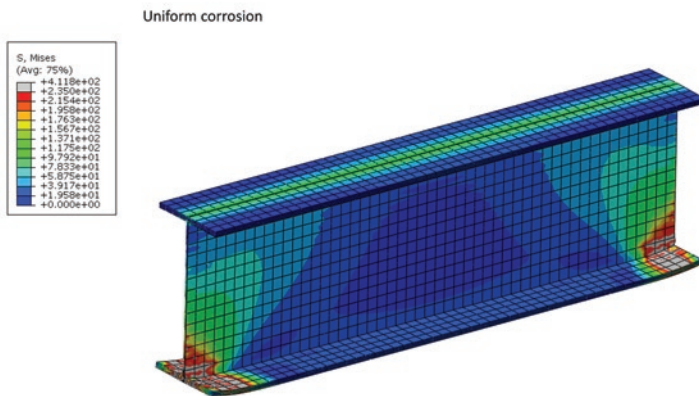


Fig. 12. Uniform corrosion by FEA method

assess the goodness of fit. A software screenshot showing the CDF of real data and fitted distributions is presented in Figure 10. The R squared value of different distributions is listed in Table 4.

In this case, the Gumbel distribution was finally selected. Other main input parameters are given in Figure 11. The design nominal thickness of the bridge girder t_{nom} was 10 mm; the minimum required thickness was directly obtained from finite element analysis (FEA), and $t_{min} = 9.18$ mm for uniform (see Figure 12); Service age was estimated to be 10 years; the return period was given as 0.95. The COF was estimated to be 'severe' if the girder failed.

The output of the software is shown in Table 5. The current risk and predicted RUL are presented on the risk matrix in Figure 13. A risk matrix would typically show the risk profile of a system of components i.e. a system of girders to support operators to prioritise inspections based on risk. In this application, for simplicity, only one girder is shown.

The final output of this software is the prediction of POF using Bayesian theory. The method of calculating the POF curves and the predicted POF after inspection can be found in Section 5.7. In this case, we assumed that the corrosion rate remained the same. The POD was 0.75 and FCR was 0.15. The POF curves when applied to bridge girder

data and Bayesian theory is shown in Figure 14. As shown in the figure, the next inspection time was after 2.8 years, and within 14 years, given the existing risk profile, there should be four inspections to keep the bridge girder safe. After every inspection, the risk profile needs to be re-calculated based on the most updated information.

5. Conclusions

This paper proposes an integrated framework to carry out the corrosion assessment via statistically analyzing thickness measurements. It is flexible and widely applicable to various engineering structures that suffer from corrosion. The methodology uses Bayesian theory to update the likelihood of the event

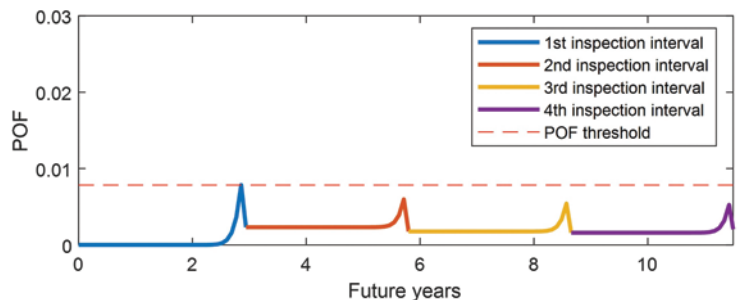


Fig. 14. POF curves when applied bridge girder data and Bayesian theory

occurrence and failure probability. The framework is aimed at supporting decision makers in optimising their asset integrity management strategy such that they can cost effectively maintain risk within tolerable levels.

The paper builds on recent work at TWI aimed at using statistical techniques on inspection data [2, 3, 6, 12]. The use of such techniques is getting increasingly common with the availability of more data. This trend has been facilitated by advances in sensor technology and computing power, and is likely to grow stronger as plant operators look for ways to improve safety and reliability of their assets.

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