CORRECTION OF PREDICTION MODEL OUTPUT–APPLICATION TO GENERAL CORROSION MODEL

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SUMMARY

This paper applies a newly developed methodology to calibrate the corrosion model within a structural reliability analysis. The methodology combines data from experience (measurements and expert judgment) and prediction models to adjust the structural reliability models. Two corrosion models published in the literature have been used to demonstrate the technique used for the model calibration. One model is used as a prediction for a future degradation and a second one to represent the inspection recorded data. The results of the calibration process are presented and discussed.

1. INTRODUCTION

The performance of marine structures is a topic of key interest to marine stakeholders (designers, shipbuilders…). Structural failures of ships contribute to the personal risk levels and safety of mariners, high pollution and economic costs.

A ship's structure is complex: a very large sophisticated and complicated beam formed by different components such as plates, stiffeners and brackets that are welded or, at one time, riveted together. These members can be grouped together according to their specific characteristics [1, 2].

During the last decades, the ship designs and construction evolved from small and medium size ships to very large ships, making the tasks of building, maintaining, inspecting and repairing the ships increasingly difficult. Most vessels experience varying degrees of corrosion and fatigue cracking, which represent the most pervasive types of structural problems.

In terms of inspections, periodic inspections are used to check for a degradation of coatings, corrosion and cracking and other material and structural deteriorations [3]. Each of the damage modes, if not properly monitored and corrected, can potentially lead to catastrophic failure or unanticipated out-of-service time. These problems are major risk to the structural integrity of the vessels, especially tanker ship structures and bulk carriers, many of which continue to operate beyond their design service life.

The knowledge gained from the past experience of ship structural inspection is crucial in order to correct and calibrate the prediction models used in the risk-based inspection and maintenance planning. The knowledge is also a key factor to consolidate any future decision. The accuracy of the data recorded from structural inspection is also very important.

A serious problem in analysing the predicted data is the model-data incompatibility caused by systematic model biases. For various reasons, even the most comprehensive models are not immune to this problem. Without an effective method to reduce the model-data mismatch, assimilating real data into the initial state of the model could result in bad initialisation, which would prevent the model from achieving its optimal predictive capabilities.

In order to make full use of the inspection data and for a better prediction of structural degradation or crack propagation, it is necessary to correct the systematic model biases. Not much attention has been paid to this problem in the past. This work will demonstrate how to effectively reduce these biases with a simple statistical correction, and the bias-corrected model can have an improved prediction performance.

This paper will discuss the application of a new calibration methodology to the corrosion degradation model for ship structures. The methodology, developed to calibrate the prediction models of structural defects using data from experience-based methods, can be used at the design stage (to improve the ship structural performance) and as a decision support system for inspection and maintenance planning in order to make inspections more cost-effective. This is presented in detail in [4] and it will be also summarised here.

To demonstrate the methodology when applied to the prediction of the corrosion propagation, a corrosion model has been selected and its outputs are calibrated by the developed methodology. A different corrosion degradation model is used to simulate "measurement data".

This paper is structured as follows: in section 2 a review of different corrosion prediction models, as well as those selected for the application of the newly developed calibration methodology are presented. In section 3 the calibration methodology is summarised. Section 4 presents the application of the methodology to the corrosion degradation prediction and discusses the results.

2. STRUCTURAL DEGRADATION MODELS

Due to the ship trade environment, the reliability deterioration of ship structures because of corrosion wastage is a widespread issue. Corrosion decreases the ability of the structures to withstand the loads and hence the level of safety of these structures diminishes with time owing to the accumulation of damage. Corrosion is considered to be one of the most important factors affecting the structural degradation of steel structures, but accurately predicting the future growth of corrosion defects requires deep knowledge of the corrosion process. This has attracted large scale research to explore and investigate the complexity of the corrosion process [5].

In addition, the importance of monitoring and mitigating corrosion (and also fatigue) has been recognized by classification societies, ship owners and the International Maritime Organizations. Standards for accessing the structural integrity of ships have been the focus of various organisations, such as the Tanker Structure Cooperative Forum (*TSCF*) which issued extensive guidelines for ageing and corroding ships [6].

Prediction models for ship structural defects and deteriorations approximate the way the structure, under certain conditions, will behave in the future. The prediction is often, but not always based on experience or knowledge. Randomness and complexity of the corrosion process is more and more addressed by statistical and probabilistic methods, but theses approaches are not often practised in the structural assessment.

There are different forms of corrosion; uniform, galvanic, crevice, pitting, intergranular, leaching, erosion and stress corrosion, which could be classified into two different classes based on the metal loss area [7]. For a uniform loss of the thickness, it can be classified as general corrosion whereas non-uniform metal loss represents localised corrosion. Corrosion rates may be reported as a weight loss or thickness loss per area divided by the time (uniform corrosion) or the depth of metal corroded, divided by the time (localised corrosion).

Yamamoto and Ikegami [8], proposed a general corrosion model assuming that the degradation phenomena is the results of three sequential processes: degradation of paint coatings, generation of pitting points, and progress of pitting points.

Linear models of corrosion growth were adopted in early studies of structural reliability considering corrosion wastage, such as Guedes Soares and Ivanov [10]. Wirsching, et al. [11], adopting a time dependent reliability formulation, and Guedes Soares and Garbatov [12] introducing a time variant reliability formulation.

Guedes Soares and Garbatov [13], proposed a nonlinear model that describes the growth of corrosion wastage in three phases: durability of the coating, transition to visibly obvious corrosion with an exponential growth, and the progress and levelling of such corrosion. In this paper, this model is used to generate simulated inspection data.

The assessment of the structural degradation should include both general corrosion and localized corrosion. Paik, et al. [9], proposed to consider the two classes of degradation as uniform, where the pitting corrosion is assumed to be equivalent to general corrosion by averaging the thickness measurement data.

Different variants to the model described above have been proposed. Sun and Bai [14], used a similar formulation presented in [13] to describe the corrosion rate instead of the corrosion wastage. Qin and Cui [15], proposed another variant to the model, where the corrosion rate is considered equivalent to the volume of pitting corrosion to uniform corrosion. The model proposed by Ivanov, et al. [16], considers a linear relationship between the increase of the transition phase of non-linear thickness reduction and the time associated.

Wang et al. [17] collected a large amount of thickness measurement data from ships in service. The data have been used to propose a regression model for corrosion wastage as function of time. Garbatov, et al. [18], have used the same service measured data, to fit to the corrosion wastage model proposed by Guedes Soares and Garbatov [13], and found that the nonlinear model has a good agreement with the data. They also derived the duration of the coating system, or in a broader sense, the time to initiation of the corrosion process.

Most corrosion wastage models have only time as parameter. To improve the corrosion models, it is also necessary to account for other contributing variables. Some environmental factors have been identified as important for the corrosion wastage of steel structures by Melchers [19]. In a more recent publication, Melchers [20] proposed a quantitative models for marine immersion which included the effect of microbiological influences in the prediction of corrosion loss and for maximum pit depth. Guedes Soares et al. [21], developed a model accounting for the effects of relative humidity, chlorides, and temperature on the corrosion behaviour of ship steel structures subjected to marine atmospheres and a new corrosion wastage model is proposed.

3. MODELS USED IN THE STUDY

For the application of the calibration methodology presented in the next section, two models for general corrosion degradation have been selected.

A first model is used to simulate the "measurements" data. A second model is used as the prediction model and its outputs will be corrected by the newly developed calibration method.

In modelling the corrosion phenomenon, it is assumed that steel plates are uniformly wasted and that corrosion does not take place in a coated structure until the coating breaks down (coating is not protecting the steel efficiently any more). After that, corrosion begins, and wastage increases over time.

Once the corrosion degradation begins, there are several types of models for corrosion progress [22] (Figure 1):

- Corrosion wastage linearly increases with time (line a). The most common and most widely used assumption in structural design.
- Corrosion increases and accelerates over time (line b) (occurs when rust build-up is disturbed).
- The rate of corrosion wastage slows down with time (line c), when the steel is gradually covered by scale and rust, protecting the new steel from a contact with the corrosive environment.
- As a variation of line c, corrosion wastage eventually approaches a plateau, which remains constant.

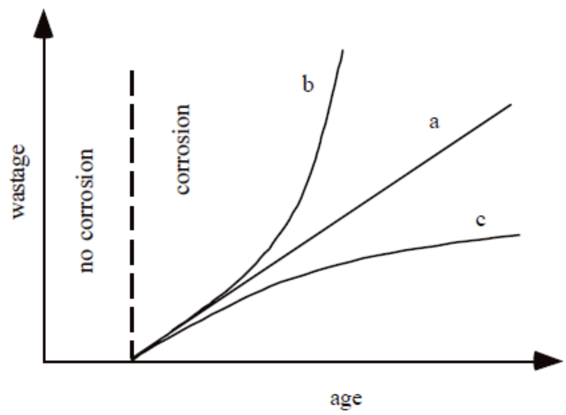

Figure 1: Models of corrosion degradation (adopted from [17])

The model used to produce measurements data is the model proposed by Guedes Soares and Garbatov [13], which describes the growth of corrosion wastage by a non-linear function of time in three phases (1st phase no corrosion as the coating protection is effective, 2nd phase wastage grows with time in a non-linear manner, 3rd phase corrosion growth levels off at a long-term value).

The model is based on the solution to the following differential equation:

$$\tau_t r(t)+d(t)=d_\infty \qquad \text{Eq. 1}$$

where d_∞ is the long term corrosion depth, d(t) is the thickness of the wastage at time t, r(t) is the corrosion rate and τ_t is the transition time during which the corrosion decreases the thickness.

The mean value and standard deviation of corrosion wastage as a function of time are then given by the following equations:

$$\mu\left[d(t)\right]=d_\infty\left[1-e^{-\frac{t-\tau_t}{\tau_t}}\right] \qquad \text{Eq. 2}$$

$$\sigma\left[d(t)\right]=a\cdot log(t-\tau_c-b)-c \qquad \text{Eq. 3}$$

τ_c is the coating life and a, b and c are coefficients defined by the regression analysis.

The long-term probability density function as a function of time is defined as a truncated normal probability density function.

A total of 14 locations is considered as follows:

bottom (1), inner bottom (2), below top of bilge - hopper tank- face (3), lower slopping (4), lower wing tank - side shell (5), below top of bilge - hopper tank -web (6), between top of bilge, hopper tank, face (7), between top of bilge, hopper tank, web (8), side shell (9), upper than bottom of top side tank, face (10), upper deck (11), upper slopping (12), upper wing tank side shell (13), upper than bottom of top side tank, web (14).

The model parameter values for each of the above locations are given in [23].

The corrosion prediction model used to simulate the observed corrosion depth is the one reported in [24] and follows a Weibull distribution probability density function given by:

$$pdf(C;k,\lambda)=\left(k/\lambda\right)\left(C/\lambda\right)^{k-1}e^{-(C/\lambda)^k} \qquad \text{Eq. 4}$$

where

$$C=\alpha(t-t_0)^\beta \qquad \text{Eq. 5}$$

C is the corrosion wastage at age t; t_0 is the year when thickness of the plates starts to deviate from the as-built condition; α and index β are constants that can be determined according to the measurement data.

The shape and scale parameters *k* and λ are functions of time and are given by:

<u>Cargo oil tanks</u>

$$\begin{cases} k=0.667+\dfrac{6.6647}{t}-\dfrac{59.1106}{t^2} \\ \lambda=0.6295+0.0383t-\dfrac{6.322}{t} \end{cases} \qquad \text{Eq. 6}$$

Ballast tanks

$$\begin{cases} k = 1.0015 + \dfrac{12.41}{t} - \dfrac{112.7036}{t^2} \\ \lambda = 0.6295 + 0.0388t - \dfrac{5.9015}{t} \end{cases} \quad \text{Eq. 7}$$

4. CALIBRATION METHODOLOGY

This section gives a brief overview of the calibration methodology and the computational steps. The methodology has been described in detail in [4].

Two approaches could be considered to effectively reduce the bias of prediction models. The first approach for model calibration is to modify or update the individual model parameters using inspection data for a given set of assumed conditions with observed data for the same conditions until the output from the model matches the observed set of data. This technique requires a lot of data about the specific parameters that is often not available.

The second approach (used in the present calibration methodology) is to consider the model as a black box (Figure 2) and to calibrate the model as a whole.

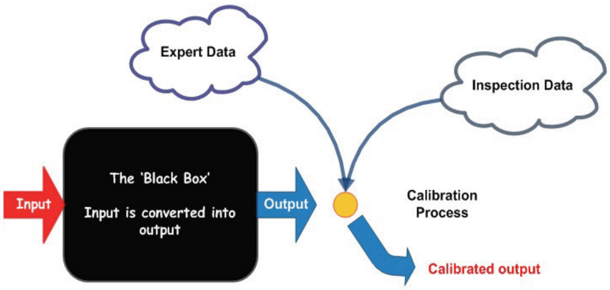

Figure 2: Black box Model

After an inspection is performed on a ship structure, each inspection result gives additional information on the in-service condition of the ship structure. The additional information leads to changes of the predicted values.

The proposed calibration methodology makes use of the inspection data and information recorded through the life of the structure and combines that with expert judgement data to calibrate (correct) the outputs of the prediction models.

The method works as follows. First the ratios obseved/predicted are computed for each location[1] according to (Eq. 1).

$$c_i = \frac{rd_i}{pd_i} \quad \text{Eq. 8}$$

Where:

- $(rd)_i$ is the recorded or measured quantity (inspection data)
- $(pd)_i$ is the predicted value (reliability/ prediction model output)

Then the mean and coefficient of variation of the ratios are calculated according to (Eq. 9).

$$c = \tfrac{1}{n} \times \sum_{i=1}^{n} c_i \quad \text{Eq. 9}$$

In the next step, the usefulness (correlation) factors (Eq. 10) according to the locations are computed from the measured data. The usefulness factor (*UF*) gives the percentage of variance in common between variables X_j and X_k.

$$UF = \rho_{jk}^2 \times 100 \quad \text{Eq. 10}$$

Where ρ_{jk} is the correlation factor between variables X_j and X_k.

Usefulness factors will also be used to evaluate the confidence in using statistical data from similar -rather than identical elements.

When more information is available the correlation can be computed based on more criteria, e.g. a particular location such as side shell, should be subdivided horizontally to have top middle and bottom parts and vertically to have right, centre and left parts (9 sections). Also steel grades, coated surfaces, environmental temperature, salinity, local fluid, flow rates… should be accounted for in the correlation computation. In other words data should be grouped according to these criteria and the correlations calculated accordingly.

For the application presented in this paper, a simple correlation (per location) has been considered.

The expert data correlations are given as input. The computational steps to obtain the calibration factors are presented next.

5. COMPUTATION STEPS

The following section presents the computational steps. The reader can find more details in [4].

Step 0: Input from prediction model.

[1] In this application both "measured" and predicted data are obtained through simulation so ratios can be computed. When dealing with real data, it is sanitised for confidentiality and sensitivity reasons. When the data is double sanitised ratios are provided as input rather than calculated.

Step 1: Determination of the ship characteristic: ship type, route, type of cargo, type of defect/deterioration (e.g.. crack)...

Step 2: Retrieve inspection and expert data with the same ship characteristic.

Inspection data:

- Measurement data for the defect/deterioration.
- Ratios Observed/Predicted if data double sanitised (when it is not possible to obtain the measured data for confidentiality matter, the methodology uses the ratios as input to compute the correction factors)

Expert Data:

- Subjective value for defect/deterioration ratio (Recorded/Predicted).
- Correlation factors for ship details.
- Correlation factors for defects.
- Ship location correlation factors.
- Ship space correlation factors.

Step 3: Computational steps

For real data (Step 3A)

- If data are single sanitised compute the ratios Recorded/Predicted else use ratios given as inputs.
- Compute measures of central tendency (averages - mean, median and mode) and measures of variability about the average (range and standard deviation) for the ratios.
- Compute the coefficient of variation.
- Compute correlation coefficients and usefulness factors.
- Perform statistical tests to help deductions to be made from the data collected, to test hypotheses set and relating findings to the group or family of the details.
- Compute confidence intervals for the mean and the coefficient of variation.
- Compute calibration factors (weighted mean) and weighted standard deviation.

For expert opinion data (Step 3B)

- Combine correlations if given separately.
- Compute confidence intervals for the mean and the coefficient of variation
- Compute calibration factors (weighted mean) and weighted standard deviation

Step 4: Combine calibration factors obtained in Step 3A (inspection data) with calibration factors obtained in Step 3B (expert data) and compute their coefficient of variation and associated confidence intervals.

Step 5: Output the calibration factors of the prediction models.

6. APPLICATION

The model used for prediction is only valid for tanks. To be able to have meaningful comparisons, 5 locations (number 3, 6, 8, 10 and 14) are considered (see above).

For the computation, similar environmental conditions are assumed for all locations.

6.1 ASSUMPTIONS AND INPUTS DATA

A period of 16 years (from10 to 25 years) was assumed. The input to represent the measurement data is obtained through simulation using the truncated normal distribution with parameters defined by (Eq 2 and Eq 3).

- For each year (year 10 to year 25) and for each location, 10^4 simulations were performed.
- For each year, predicted values for the same locations were also computed using the cargo tank equation of the prediction model (Eq 5).
- Expert data was assumed to come from 100 inputs.

Once the correlations were obtained, four different cases were assumed to compute the calibration factors as follows:

- ***Case 1;*** only expert data is available for the 5 locations;
- ***Case 2:*** two (locations 3 and 6) of the five locations have, in addition to expert data, measurement data available for each year starting from year 10 to year 25;
- ***Case 3:*** four of the five locations have both expert and measurement data available for each year starting from year 10 to year 25, and the remaining location (location 14) has only expert data;
- ***Case 4:*** all locations have both expert and measurement data available for each year starting from year 10 to year 25.

Calibration factors and the corresponding coefficients of variation of the expert data remain the same for all 4 cases defined above and are given, per year and per location, respectively in Table 1 and Table 2.

6.2 GENERAL CORROSION RESULTS AND DISCUSSION

Different sets of measurements and prediction data to those used to compute the calibration factors were used to demonstrate the calibration process.

Graphical representations of the results of the prediction models calibration, per location, over the considered period of time (for 10 to 25 years) are shown in Figure 5 below and Figure 6 to Figure 9 in the Appendix.

When looking at Figure 5 to 9, it can be noticed that calibration of the prediction models is improved when measurement data are available (case 4) compared to when, only, expert data are available (case 1).

In case 1 the calibrated curve is closer to the inspection data curve when compared to the predicted curve but has a different shape. Whereas in case 4, the calibrated curve is almost superimposed to the measurement curve.

There are few noticeable differences between the locations though.

For location 14, where expert data is the only available data in all cases apart from case 4, the calibrated curve remains practically the same in case 1, 2 and 3. This could be explained by the fact that the usefulness factors of the data from the other locations are very low so they do not influence the calibration factor. In case 4, the measurement data for location 14 is available and its usefulness factor is 100 so its influence on the calibration factor is stronger than the rest of the information coming from the other locations. This explains the improvement in the calibrated curve in case 4 (Figure 5).

For location 10, measurement data are available in cases 3 and 4. This is reflected by the calibrated curve, which is almost the same for case 1 and case 2, but is improved (gets closer to the inspection curve) when measurements data is available. A slight improvement is also observed in case 4 where measurement data is available in all locations. The same pattern of results is observed for location 8.

Location 6 and 3 share similar patterns too. There is a clear improvement of the calibrated curve between case 1 and case 2. Case 3 and 4 are also quite similar in terms of closeness of the calibrated curve to the measurement curve with a slightly better agreement in case 4 in both locations.

Coefficients of variation of the calibration factors in each case, for each location and for each year, have also been computed. Detailed results can be found in [25].

When measurement data is available the coefficients of variations decrease significantly (on average 75% decrease when comparing case 1 and case 4) meaning that measurement data provide additional confidence in the calibration factors.

The data used to demonstrate the calibration process is simulated data and the correlation factors (usefulness factors) were computed only based on one criterion of "location". Nevertheless, this is useful for demonstrating the methodology, and show how the calibration procedure works.

Table 1: Expert data corrosion mean depth per location as a function of time and year in (mm)

Year	Location 14	Location 10	Location 8	Location 6	Location 3
10	2.655	2.875	4.364	4.152	4.332
11	2.602	2.817	4.277	4.069	4.245
12	2.549	2.76	4.189	3.986	4.159
13	2.496	2.702	4.102	3.903	4.072
14	2.443	2.645	4.015	3.820	3.985
15	2.389	2.587	3.928	3.737	3.899
16	2.336	2.53	3.84	3.654	3.812
17	2.283	2.473	3.753	3.571	3.726
18	2.230	2.415	3.666	3.488	3.639
19	2.177	2.358	3.578	3.405	3.552
20	2.124	2.30	3.491	3.322	3.466
21	2.071	2.243	3.404	3.239	3.379
22	2.018	2.185	3.317	3.156	3.292
23	1.965	2.127	3.229	3.072	3.206
24	1.912	2.07	3.142	2.989	3.119
25	1.858	2.012	3.055	2.906	3.032

Table 2: Coefficient of variation for expert data per location as a function of time and year

Year	Location 14	Location 10	Location 8	Location 6	Location 3
10	1.143	0.945	1.024	1.121	1.194
11	1.154	0.954	1.034	1.132	1.206
12	1.166	0.964	1.044	1.143	1.218
13	1.177	0.973	1.054	1.155	1.230
14	1.189	0.983	1.064	1.166	1.242
15	1.200	0.992	1.075	1.177	1.254
16	1.212	1.002	1.085	1.188	1.266
17	1.223	1.011	1.095	1.199	1.278
18	1.234	1.021	1.105	1.211	1.290
19	1.246	1.030	1.116	1.222	1.302
20	1.257	1.040	1.126	1.233	1.314
21	1.269	1.049	1.136	1.244	1.326
22	1.280	1.058	1.146	1.256	1.338
23	1.292	1.068	1.157	1.267	1.350
24	1.303	1.077	1.167	1.278	1.362
25	1.314	1.087	1.177	1.289	1.374

7. CONCLUSIONS

This paper has presented a newly developed methodology to calibrate the prediction models of structural defects and deteriorations using data from experience-based methods and expert judgement. The paper has presented an example application of the calibration methodology. The different computation steps were demonstrated using two different corrosion prediction models. The first one to simulate the inspection (measurement) data and the second one was used as a prediction model. The calibration factors were computed and the results of the calibrated curves presented.

The results have clearly demonstrated an improvement of the predictions when measurement data were available. The calibrated curves moved closer to the measurement curves when measurements were used to compute the calibration factors.

The methodology demonstrated herein is to be used to improve risk-based inspections and maintenance planning and make them cost-effective. The proposed methodology is inherently adaptable and can be applied to many other applications that require model correction for effective results.

8. ACKNOWLEDGEMENTS

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10. APPENDIX

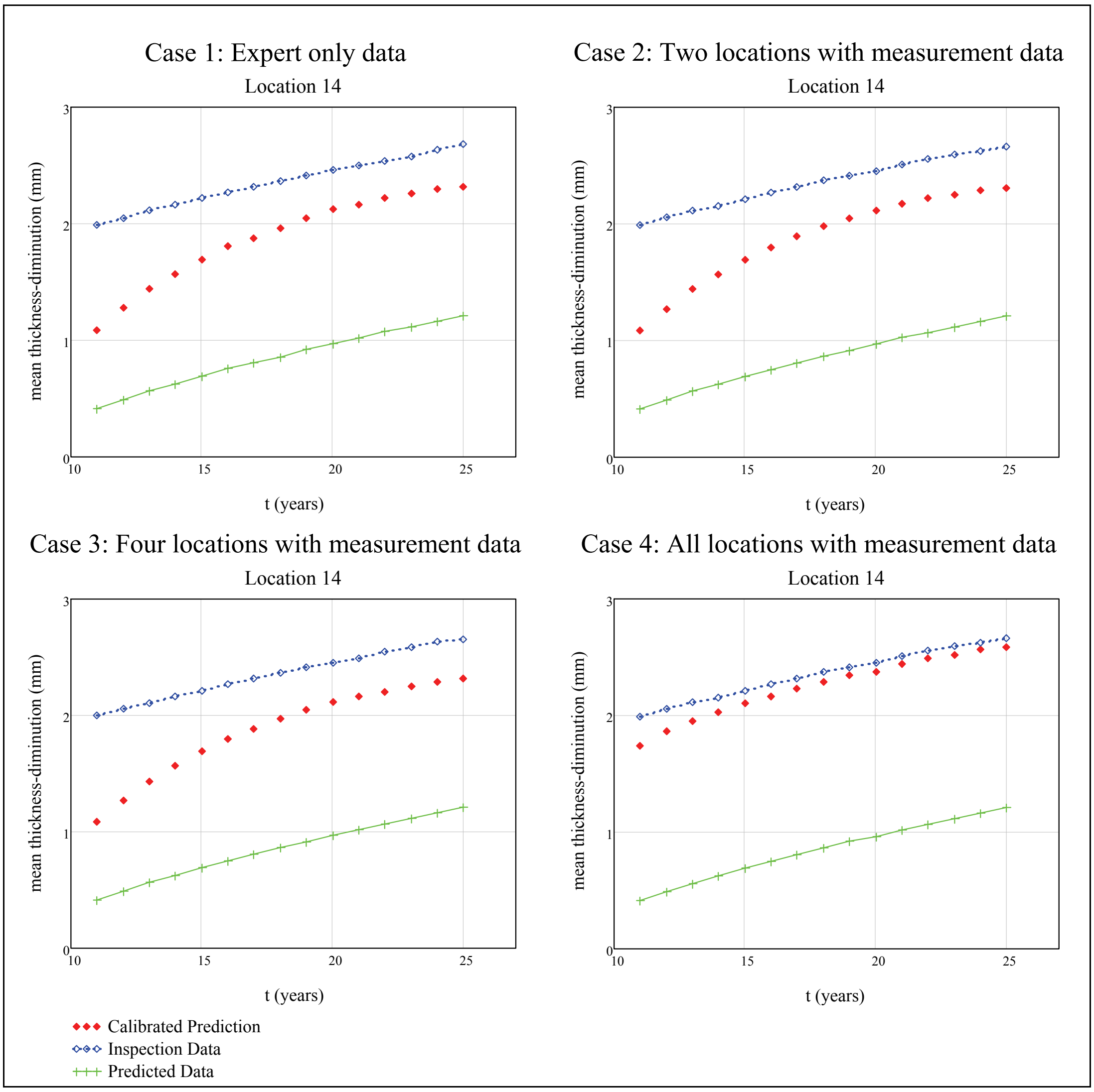

Figure 5: Predicted data, measured data and calibrated data of corrosion depth for location 14

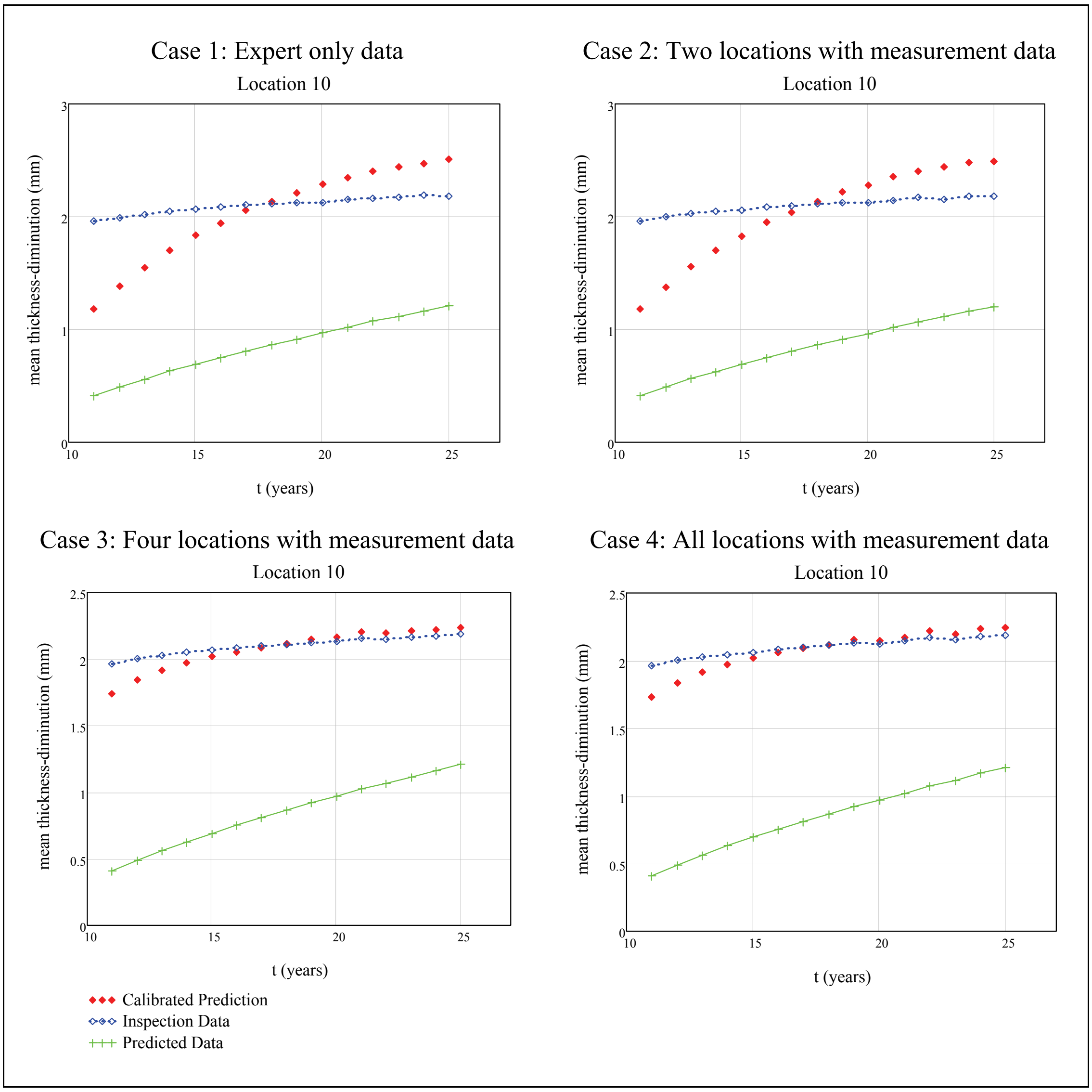

Figure 6: Predicted data, measured data and calibrated data of corrosion depth for location 10

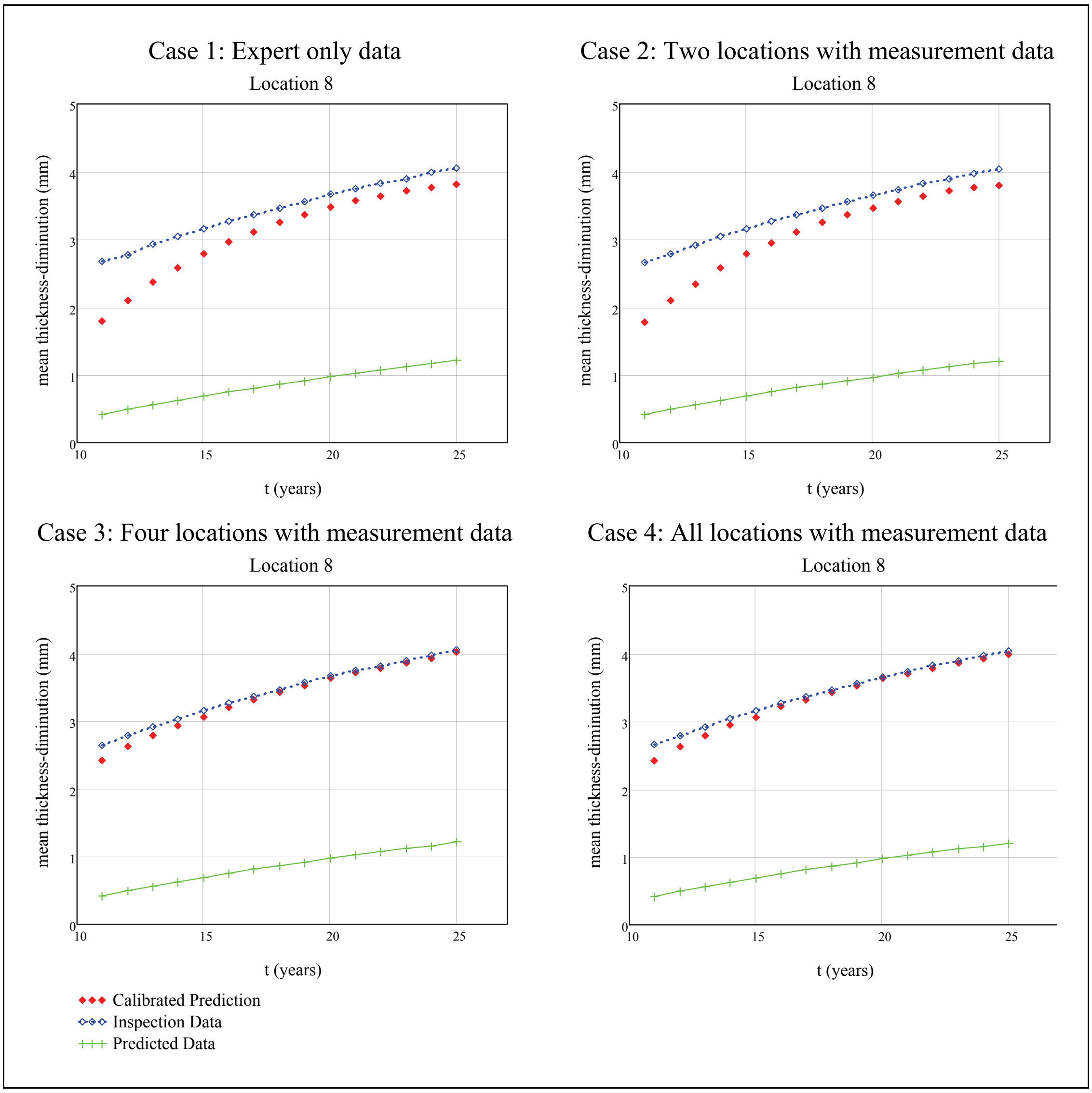

Figure 7: Predicted data, measured data and calibrated data of corrosion depth for location 8

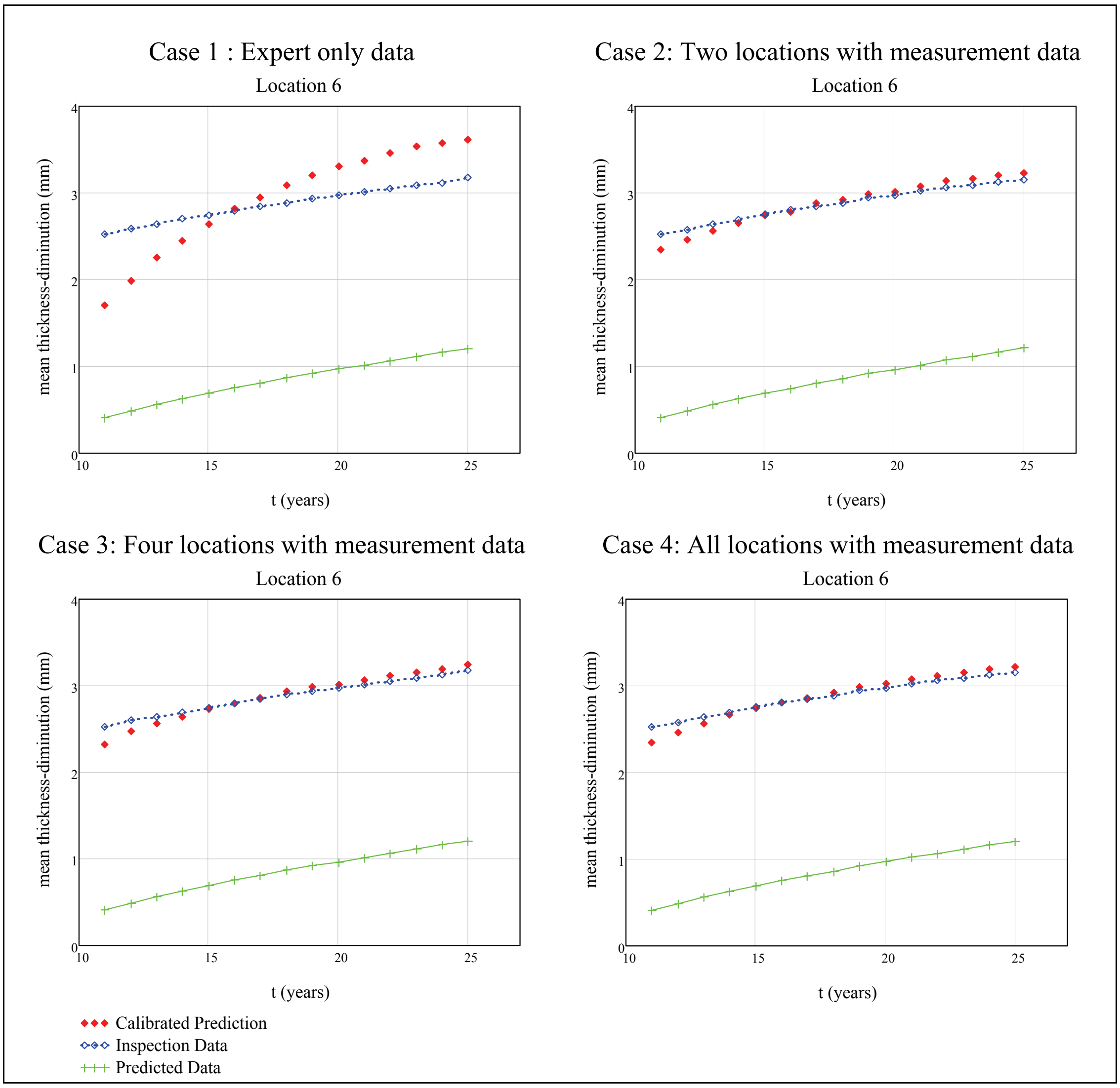

Figure 8: Predicted data, measured data and calibrated data of corrosion depth for location 6

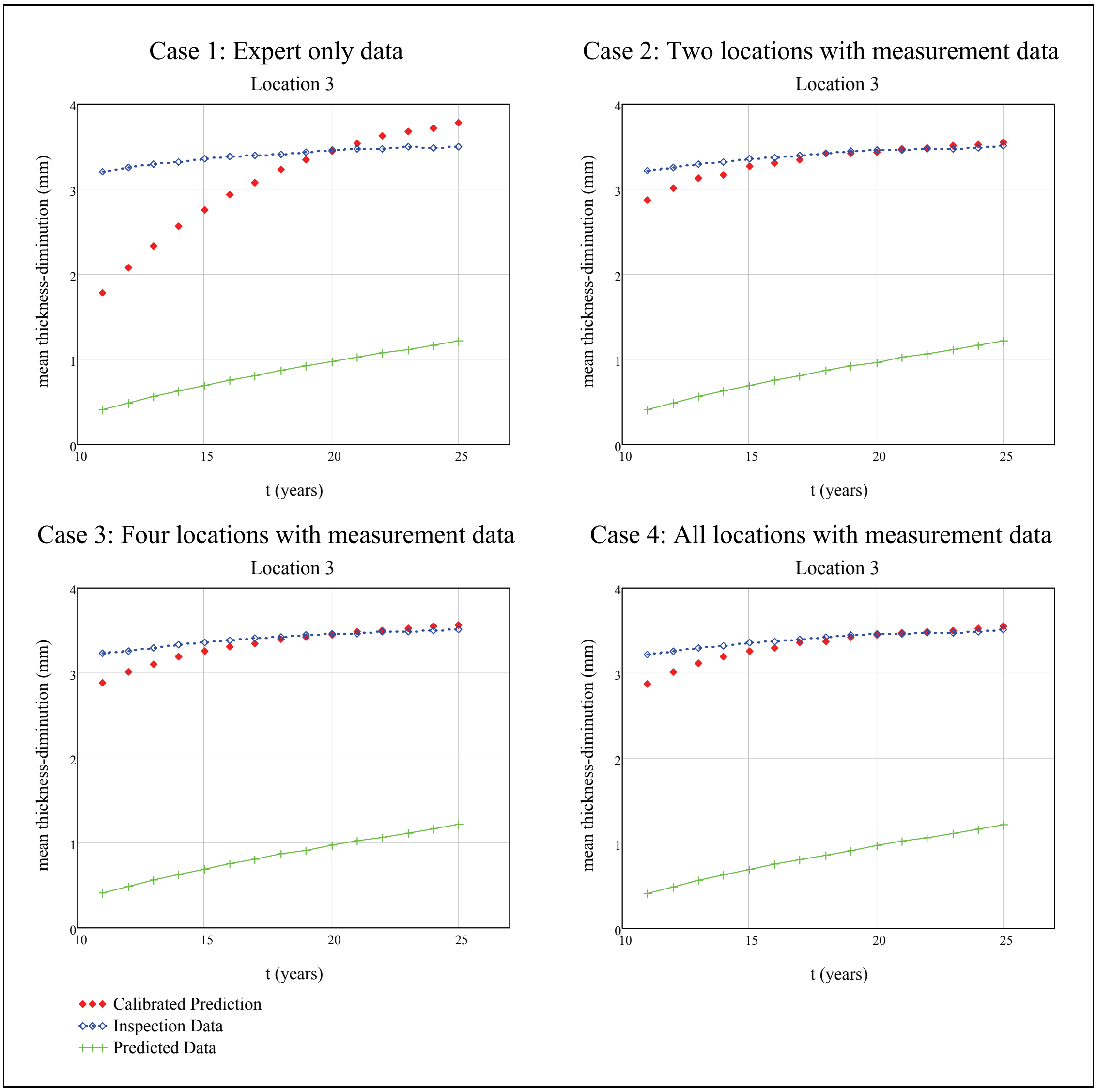

Figure 9: Predicted data, measured data and calibrated data of corrosion depth for location 3