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Extreme value analysis (EVA) of inspection data and its uncertainties

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ABSTRACT

Extreme value analysis (EVA) is a statistical tool to estimate the likelihood of the occurrence of extreme values based on a few basic assumptions and observed/measured data. While output of this type of analysis cannot ever rival a full inspection, it can be a useful tool for partial coverage inspection (PCI), where access, cost or other limitations result in an incomplete dataset. In PCI, EVA can be used to estimate the largest defect that can be expected. Commonly the return level method is used to do this. However, the uncertainties associated with the return level are less commonly reported on. This paper presents an overview of how the return level and its 95% confidence intervals can be determined and how they vary based on different analysis parameters, such as the block size and extrapolation ratio. The analysis is then tested on simulated wall thickness data that has Gaussian and Exponential distributions. A curve that presents the confidence interval width as a percentage of the actual return level and as a function of the extrapolation ratio is presented. This is valid for the particular scale parameter (σ) that was associated with the simulated data. And for this data it was concluded that, in general, extrapolations to an area the size of 500–1000 times the inspected area result in acceptable return level uncertainties (<20% at 95% confidence). When extrapolating to areas that are larger than 1000 times the inspected area the width of the confidence intervals can become larger than 30–50% of the actual return level. This was deemed unacceptable: for the example of wall thickness mapping that is used throughout this paper, these uncertainties can represent critical defects of nearly through wall extent. The curve that links the confidence interval width to the return value as a function of extrapolation ratio is valid only for a particular scale parameter value of the EVA model. However, it is imagineable that a few of such relations for different scale parameters σ could be simulated. By picking the relation with the closest σ value (based on observation or estimation) for the inspection dataset, the presented approach can then be used to quickly estimate the uncertainty associated with an EVA extrapolation.

1. Introduction

Statistical modelling is an important tool in many areas of science and engineering. It has been used in a wide range of applications from quantifying the uncertainty of the output of a measurement tool [1] to predicting the lifetime of engineering components [2,3]. In non-destructive testing (NDT), specifically, statistical modelling has been used to study the probability of missing critically sized defects in an inspection [4], studying the reliability of inspections [5,6] and the probability of component failure [7]. A statistical model describes the behaviour of a random variable, providing a probability of a given value of the random variable occurring. While the statistical tools described in this paper are not limited to a particular problem, this paper illustrates their use by application to a particular problem: assessment of wall loss due to corrosion from ultrasonic inspection data. For this particular application area coverage is very important. Often full coverage of a plant/component cannot be achieved due to cost, access or other limitations. Therefore partial coverage inspection (PCI) is required. PCI is based on the construction of a statistical model from inspection data collected across a sample area (as illustrated in Fig. 1). The findings from the sample area are then used to form a picture of the condition of a larger area or the whole component. In the particular case that we focus on in this paper the random variable is the measured thickness (or the wall loss) across the inspection area and the operator is particularly interested in the largest defect (the thinnest wall thickness that is to be expected/measured).

Fig. 1 shows that the key contribution of the statistical model is the extrapolation of information from the known domain (inspected area) to the full region of interest (area to which one extrapolates). There are different ways of carrying out this extrapolation, it can be done based on the cumulative distribution function (CDF) of measured thickness values or based on a sample of minima within sub-populations of the

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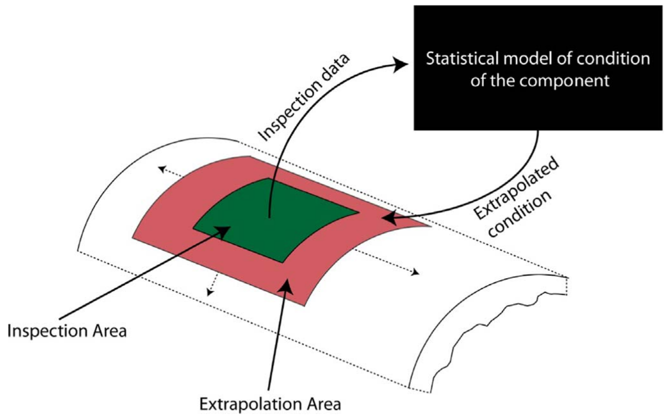


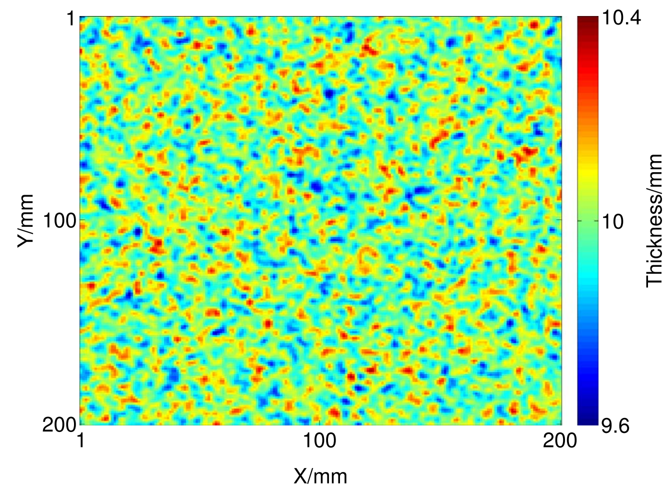
Fig. 1. An example partial coverage inspection. A data analyst uses data that was collected from the green area to construct a statistical model. The statistical model (represented by a black box) is used to extrapolate to the condition of the larger red area. Hypothetically this area could be as large as the entire component.

available data population, extreme value analysis (EVA) is an example of the latter. The key difference between the two approaches is that the CDF is a model that focuses on describing the whole thickness distribution, whereas EVA focuses more tightly onto the extremes (in this case the largest defects/thinnest part of the wall).

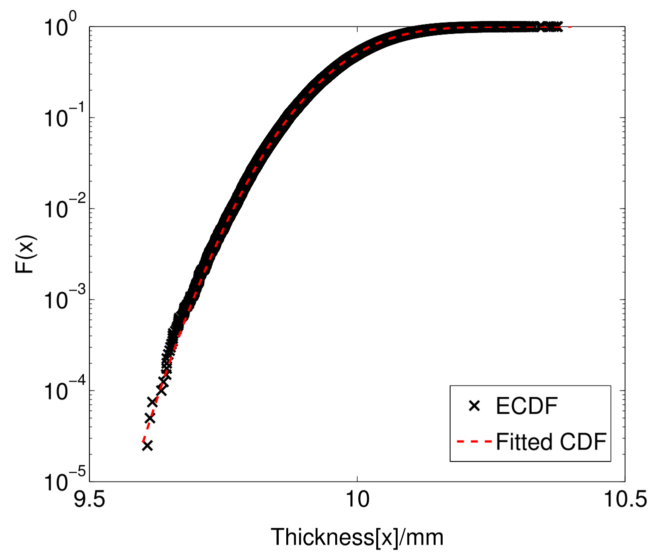
The study of extreme values is a well-developed topic, finding applications to topics as varied as finance [8,9], structural design [10–12], environmental modelling [13,14] and even the assessment of the risk of terrorist attacks [15]. Its use for analysis of corrosion data is discussed in [3]. Kowaka provides a number of examples of the use of extreme value analysis to extrapolate from C-scans of reduced areas of a plant to larger areas of components. Further examples are provided in [16–29]. EVA gained some traction in Japan in the 1970s. However, it then fell out of favour. The authors believe that this might have been due to the lack of available computational power which made processing large amounts of C-scan data infeasible.

In recent years, the use of an extreme value approach has regained popularity. A report prepared for the Health and Safety Executive (in the UK) assessed current available methods and the barriers to their adoption. It concluded that there are readily available statistical methods for the analysis of corrosion data. However, these methods are not used due to poor dissemination to engineers and the lack of any readily available computational tools [30]. There is also a lack of knowledge about the uncertainties of EVA predictions and this paper aims to address this.

This paper is structured as follows: first the theoretical framework behind the cumulative distribution function and EVA are outlined and the process of extrapolation from the known data is described. Following this a method of determining the confidence intervals of the return level is described. Then 3 different numerical studies are presented: The first study demonstrates that EVA and the return level are an effective way of estimating the minimum thickness when extrapolating from an inspected area to a larger area over which an assessment is made. Simulated inspection data is used to show to compare the minimum thickness values in actual thickness distributions to those estimated by the return level method. The second study investigates the variation of the confidence interval width as a function of the block size (number of thickness minima) and the extrapolation ratio that are used in the EVA. The third study highlights the trade off between precision (confidence interval width) of an EVA prediction and the accuracy of the prediction, specifically with regards to the number of minima that are used to construct the EVA model. In order to do so groups of actual minimum thicknesses from very large surfaces and their EVA estimates are compared. Then results are summarised and conclusions are drawn.



(a)



(b)

Fig. 2. (a) A thickness map of a Gaussian distributed Gaussian correlated rough surface with RMS=0.1 mm and correlation length 2.4 mm. (b) The empirical cumulative distribution function extracted from the thickness map above. The black crosses are the estimated values of the cumulative distribution function while the red dashed line is a Gaussian distribution that has been fitted to the data.

2. Background theory

2.1. The cumulative distribution function

Ultrasonic inspection data of corroded components usually comes in the form of a C-scan thickness map (Fig. 2(a)). The thickness at each position in the map is represented by a coloured pixel, providing a qualitative overview of the degradation in the inspection area. The thickness map can be converted into a more quantitative presentation of the data by calculating an estimate of the cumulative probability distribution of the thickness measurements. This is calculated by sorting the thickness measurements in ascending order, assigning each thickness measurement a rank and using this rank to calculate the empirical cumulative distribution (ECDF) function:

$$F(x) = \frac{i}{N+1} \quad (1)$$

where x is a measurement of thickness, i is its rank and N is the total number of thickness measurements. $F(x)$ is the probability of measuring a thickness of less than x. An example of a cumulative distribution