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Sample selection for extreme value analysis of inspection data collected from corroded surfaces

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ABSTRACT

Inspection of corroded engineering components is vital for ensuring safety throughout the lifetime of infrastructure. However, full inspection can be infeasible due to time constraints, budgetary limits or restricted access. Subsequently there is growing interest in partial coverage inspection (PCI) techniques which use data from the inspection of a limited area to assess the condition of larger areas of a component. Extreme value analysis (EVA) is a tool for PCI, it allows an inspector to build a statistical model of the smallest thicknesses across a component. Construction of extreme value models relies on the selection of the smallest thicknesses from the inspection data. Current methodologies rely on the judgement of the analyst to select sets of thickness minima and frequently the inspection data is not checked to ensure that the assumptions made by EVA are reasonable. Consequently, the resulting models can be subjective and can provide inadequate models for extrapolation. In this paper, a framework for building extreme value models of inspection data is introduced. The method selects a sample of thickness minima such that the data is compatible with the assumptions of EVA. It is shown that this framework can select a suitable set of minima for a large number of correlated exponential and Gaussian surfaces and the method is tested using real inspection data collected from an ultrasonic thickness C-scan of a rough surface.

1. Introduction

Corrosion costs the petroleum industry in the United States of America around $8 billion *per annum*[1]. Accurate assessment and tracking of corrosion related degradation is vital to ensure smooth operation of facilities and to prevent accidents [2]. The condition of a facility is assessed using regular inspections performed by experienced and independent contractors. Often regular shut down periods are scheduled to allow for these inspections, some of which require access to hazardous areas of the plant. Furthermore, despite all efforts full inspection is not always possible because of access problems (other plant components concealing the area, scaffolding or excavation required for the inspection), time constraints in shut down periods and limited inspection budgets.

Risk based inspection (RBI) strategies are becoming commonplace in asset management [3]. Certain areas are more safety critical or degradation mechanisms (such as corrosion) are known to be more aggressive in particular parts of the plant. These areas are considered at higher risk than others. Therefore, to be most economical, asset owners prioritise inspections in these sample areas. Sometimes inspectors can only access a fraction of these areas. In this situation partial coverage inspection (PCI) can be used to estimate the worst case damage in the whole structure based on the data that is available. PCI builds a statistical model of the condition of an inaccessible area using the inspection data from accessible areas of a component (an example thickness map is shown in Fig. 1a) which are exposed to the same operational and environmental conditions. This approach is attractive as it has the potential to estimate the condition of very large areas of a component using small samples of data. The technique can be applied to data from conventional inspection techniques such that all existing sensing technologies can be used.

Examples of applications of PCI to real ultrasonic thickness inspection data can be found in Stone [4]. Stone calculated the empirical cumulative distribution function (ECDF) of thickness measurements collected as part of real inspections (an example of which is shown in Fig. 1b). The ECDF is an estimate of the probability of measuring a thickness of a given value, which can be interpreted as the fraction of the area with a thickness of less than a given value. For example, if an ECDF gave an estimate of probability of 0.1 for a thickness measurement, then 10% of the component area would have a thickness smaller than this. Stone shows that the estimates of probabilities of the thickness measurements calculated from

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0010-938X/

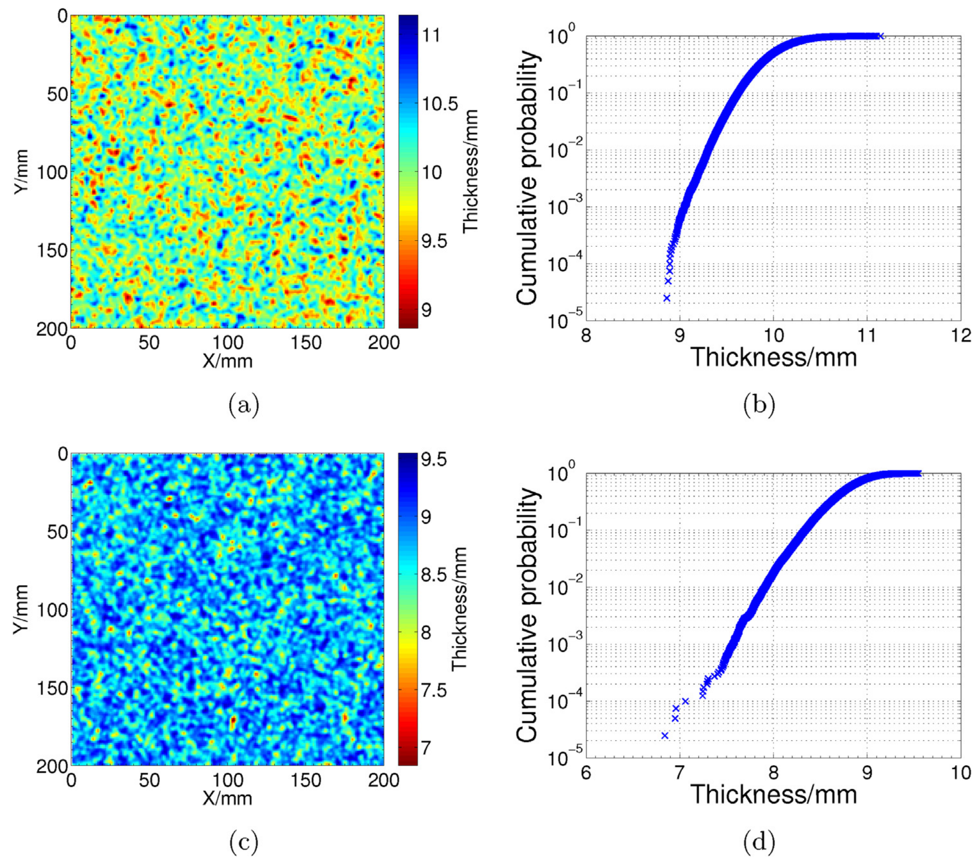

Fig. 1. (a) An example thickness map of a correlated Gaussian surface with RMS height 0.2 mm and correlation length 2.4 mm, showing the position of each measurement with each point colour coded proportional to its magnitude. (b) The empirical cumulative distribution function calculated from the Gaussian thickness map. The ordinate axis shows the probability of measuring a thickness of less than the corresponding value on the abscissa. (c) An example thickness map of a correlated exponential surface with RMS height 0.2 mm and correlation length 2.4 mm (d) The empirical cumulative distribution function calculated from the exponential thickness map.

different inspections of the same area can be very different [4]. These variations lead to different estimates of the fraction of the area of the component covered by the smallest thickness measurements. In order to build an accurate picture of the condition of the uninspected area one needs to take into account the variation which arises from sampling the smallest thickness measurements.

A key part of this problem is that an inspector only has access to data from a small inspected area. In this area, there is only one minimum thickness, which does not provide enough information to build a model of the smallest thicknesses. An inspector can generate a sample of the smallest thickness measurements by partitioning the inspection data into a number of equally sized blocks. In each block the minimum thickness is recorded. This set forms a sample of the smallest thickness measurements. From this sample, one can build a model which takes into account the variations of the smallest thickness measurements. Extreme value analysis (EVA) provides a limiting form for this model. It states that, if the underlying thickness measurements in each block are taken from independent and identical distributions, then the sample of minimum thickness measurements will follow a generalized extreme value distribution (GEVD).

The GEVD makes it possible to calculate the probability of measuring a minimum thickness of less than a given value. This has inherent value to both the plant operator and the inspector. The model allows the inspector to report both the smallest thickness they have found and a probability of finding a minimum thickness less than this value in the uninspected areas of the structure. Potentially, a plant operator can make decisions about inaccessible areas of a plant. For example, Schneider used EVA to model the condition of an inaccessible area of a pipework system on an oil platform [5]. EVA allowed Schneider to calculate estimates of the probability of future leaks in the inaccessible area based on inspections of the accessible area. Kowaka and Shibata give similar examples of the application of EVA, ranging to generating a probability distribution for pit depths in steel piles in sea water to calculations of the most likely maximum pit depth in an oil tank [6,7].

The problem with existing applications of EVA to corrosion data is that the analysis is dependent on the judgement of the analyst and does not necessarily check that the data is suitable for EVA (i.e. they do not check that there is evidence the assumptions made by EVA are fulfilled). For example existing methods for selecting a suitable block size have focussed on examining the fit of the GEVD to the set of minima selected using that block size. Glegola selected a block size by extracting sets of thickness minima using multiple block sizes [8]. For each set of minima the quality of the fit to the GEVD was examined and the block size which gave the best fit to the GEVD was used for the analysis. Another example is the work by Schneider, who selected a block size to ensure that the minima from each block were independent [5], however he did not confirm the identicalness of the distributions in each block. Schneider examined the two dimensional autocorrelation function of the thickness map and chose a block size, L, such that thickness measurements separated by L were weakly correlated. In contrast to Glegola's method this approach chooses a block size based on one of the assumptions of EVA.

However, in addition to the independence of thickness measurements, EVA also assumes that that probability distribution of