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ScienceDirect
NDT&E International 39 (2006) 661–667
NDT&E international
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MFL signals and artificial neural networks applied to detection and classification of pipe weld defects

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Received 20 January 2006; received in revised form 7 April 2006; accepted 10 April 2006
Available online 5 June 2006

Abstract

This work evaluates the use of artificial neural networks (ANNs) for pattern recognition of magnetic flux leakage (MFL) signals in weld joints of pipelines obtained by intelligent pig. Initially the ANNs were used to distinguish the pattern signals with non-defect (ND) and signals with defects (D) along of the weld bead. In the next step the ANNs were applied to classify signal patterns with three types of defects in the weld joint: external corrosion (EC), internal corrosion (IC) and lack of penetration (LP). The defects were intentionally inserted in the weld bead of a pipeline of API 5L-X65 steel with an outer diameter of 304.8 mm. In this way, the MFL signal itself, digitized with 1025 points, was used as the ANN input. Initially the signals were used as inputs for the neural network without any type of pre-processing, later four types of pre-processing were applied to the signals: Fourier analysis, Moving-average filter, Wavelet analysis and Savitzky–Golay filter. Signal processing techniques were employed to improve the performance of the neural networks in distinguishing between the defect classes.

The results showed that it is possible to classify signals of classes D and ND using ANN with very efficient results (94.2%), as well as for corrosion (CO) and LP signals (92.5%). Also it is possible to classify the defect pattern signals: EC, IC and LP using neural networks with an average rate of success of 71.7% for the validation set.

Keywords: Non-destructive inspection; Pig; MFL; Neural network; Pattern recognition

1. Introduction

Pipelines are considered the most efficient way of transferring fluids (oil and gas) over long distances. However, despite this high-efficiency, there has been reasons for concern over the last years, principally because a large part of the existing pipeline networks are coming to the end of their useful life. Consequently it is necessary to be able to monitor, evaluate and to guarantee their structure as a whole, taking precautions against leaks and consequently protecting the environment and the population. Non-destructive tests (NDT) coupled with signal processing techniques and artificial intelligence, such as artificial neural network (ANN), have contributed positively to evaluate the structural integrity of the pipelines used by the petroleum industry.

The non-destructive inspection of pipelines for fluid transport is based principally on the magnetic flux leakage (MFL) technique, for the detection of discontinuities and loss of thickness due to corrosion (CO) of the pipeline walls, permitting a quantitative evaluation of the size of the defect [1–3]. The MFL technique uses a tool known as intelligent pig to inspect pipelines. The pig is propelled inside the pipe under the pressure of the fluid and it is equipped with various sensors to gather information on the state of the pipeline, Fig. 1. For pipelines that are buried, offshore or of difficult access this pig method is the only

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0963-8695/$ - see front matter
doi:10.1016/j.ndteint.2006.04.003

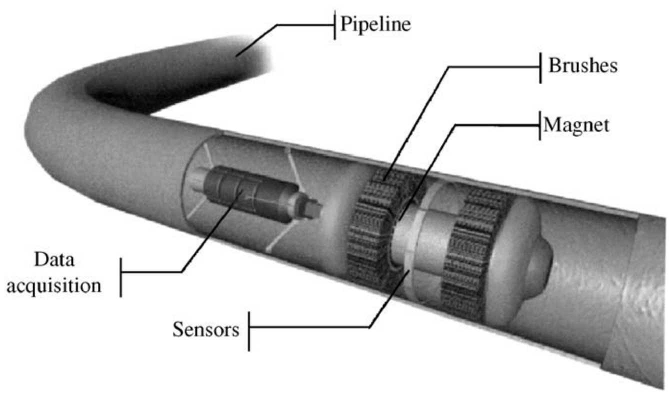

Fig. 1. Sketch of a magnetic pig.

possible option for inspection. Today there are two well-known techniques for pig inspection: ultrasonic and MFL, however approximately 90% of the inspections via pig are carried out using the MFL magnetic pig [1].

The MFL technique, if on the one hand, has a high probability of detecting defects, on the other, its ability to classify these defects is still questionable, since it is difficult to correlate the signal characteristics to the type of defect. Normally the classification of the signal is carried out visually; and so this basically depends on the ability and knowledge of the operator. However, the correct classification of the type of discontinuity on the pipeline wall would allow a faster and more precise decision to be made in terms of repairing the damage, reducing the risk of failures and consequently any temporary production loss or negative environmental impact.

The innovative growth of computational techniques, mainly in sciences related to artificial intelligence, like neural networks, has given a great impulse in the development of automatic inspection and classification systems of defect patterns [4–7]. In this work, the pattern classifiers used ANNs to recognize the classes of the MFL signals from intelligent pig inspection of weld joints. The performance of these classifiers was initially evaluated for the signal classification of defects (D) and non-defects (ND) and later for three types of defects of weld joints—external corrosion (EC), internal corrosion (IC) and lack of penetration (LP)—which were artificially introduced in the weld bead. Pre-processing techniques, such as Fourier analysis [8,9], wavelets transform [10,11] and Savitzky–Golay filter [12,13], were applied to the network input signals in an attempt to facilitate the automatic classification.

2. Methodology

2.1. Specimens

For the present study four specimens were prepared (S1, S2, S3 and S4) from seamless steel pipes with the specification API 5L-X65, having a length of 9100 mm, nominal outer diameter of 304.8 mm and wall thickness of 7.1 mm. On these specimens 12 circumferential welds were made with defects artificially inserted during the welding process (Fig. 2). Three classes of defects were simulated in the weld bead: EC, IC and LP. The defects were inserted at each 90° along the weld bead resulting in a total of four defects per bead, as seen in Fig. 2. The LP defect was introduced during the welding of the bead while the EC and IC defects were simulated with shallow groves inserted manually by machining (Fig. 3). The defects had depths varying between 3 and 5 mm and lengths varying between 10 and 50 mm.

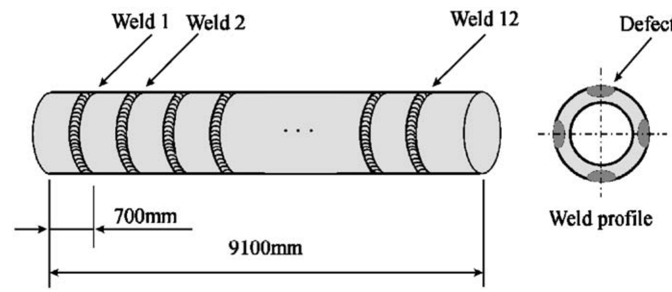

Fig. 2. Specimen used in the tests.

2.2. Tests with MFL pig

Intelligent pigs have electronic instrumentation adequate for each method of inspection for the measurement or recording of parameters to appraise the state of the pipeline. The use of intelligent pigs enables access to underground and subsea pipelines, which would be impossible using conventional inspection methods. An additional advantage of using pigs is that the inspection can be carried out during normal pipeline operation without causing any stoppages. Besides the sensors, pigs are equipped with units for acquisition, data processing and energy sources, and are able to travel for hundreds of kilometers while submitted to high pressures and in contact with the pipeline fluid [14–17].

The principle of MFL pig inspection is based on the application of a known external magnetic field onto a ferromagnetic material and measuring the response via appropriate sensors (Hall sensors or coil). If the material presents any discontinuity on its surface or interior, the external magnetic field will be disturbed, being the type of disturbance dependent on various factors, such as the intensity of the magnetic field applied, the geometry of the defect, the type of material, etc. [18,19], as shown in Fig. 4.

In this work it was used an MFL pig with 136 Hall sensors and a ring of coil type sensors, used to discriminate between internal and external defects.

2.3. Artificial neural networks

An ANN is a simple mathematical model whose purpose is to represent the human brain behavior in different situations [21]. This mathematical model consists of a generic interpolation equation that is function of the