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Empirical structure for characterizing metal loss defects from radial magnetic flux leakage signal

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ABSTRACT

Magnetic flux leakage (MFL) technique is one of the oldest and most commonly used technique for detecting corrosion in the pipe wall as well as pipeline features like welds, valves, supports, attachments, etc. The MFL data obtained is processed for detecting (isolating) defect or feature signal and characterizing it for the purpose of sizing or assigning a template. This paper discusses the methodology adopted for analysis of radial MFL signal. The characterization of the defects is based on primary and secondary parameters of the radial MFL signature. Primary parameters are axial and circumferential spread and amplitude of the signature. In addition, secondary parameters like shape and extent of the signature are also considered. Accuracy and confidence of sizing achieved by the proposed scheme are validated by several dig site inspections of actual buried oil pipelines.

1. Introduction

Corrosion and stresses causing catastrophic failures are major problems for underground pipelines carrying petroleum products. Although protected by other methods such as coating and cathodic protection (CP), it is mandatory to do inline inspection of the pipelines by Instrumented PIGs (IPIG) at regular intervals. Preventive maintenance based on the in line inspection (ILI) report avoids accidental loss of highly inflammable and costly petroleum products. Instrumented pigs work based on either magnetic flux leakage (MFL) or ultra-sonic (UT) principle. The main advantage of MFL technology over UT is that the former requires no coupling medium for sensing and hence can be used for both liquid and gas pipelines. The characterization technique proposed in this paper, however, is restricted neither to underground pipeline nor to the nature of the product carried by the pipelines. The structure of the rules used for characterization is as such general in nature and is independent of the diameter and thickness of pipelines, as long as the pipe wall is saturated to an optimum level of magnetization. In both cases, a large volume of data from an inspection run is needed to be analyzed in a short time. Moreover, accurate detection and characterization of defects for final assessment of pipeline health are extremely important. The task can only be managed with very efficient automation, reducing the time for offline assessment as well as maintaining the reliability of the analysis [1]. This paper presents a complete solution for characterizing the defects as well as pipe features based on radial MFL data in a step by step approach.

The MFL tool comprises of permanent magnets to magnetize the pipe wall and an array of hall-effect sensors mounted around the circumference to measure the leakage flux density [2,3]. As the instrument moves along the pipeline propelled by the product flowing in the pipeline, the hall sensors sense the leakage flux density continuously and the outputs are acquired, digitized and stored in the on-board data acquisition system of the instrument. Prior to storage, the data collected by IPIG is processed on-line by thresholding its projections on a set of wavelet basis, to retain useful information regarding pipe features and metal loss defects. The compressed MFL data is de-compressed and de-noised offline using discrete wavelet transform (DWT) to form an image of the pipe surface. Pipe features and defects are detected from the pipe image using image segmentation technique. Signal features are extracted from the detected defect signature and are mapped onto defect features. The three primary signal features detected are axial extent of signal termed as span, circumferential spread of signal in terms of number of sensors and maximum peak to peak gauss level for a particular feature. In addition to these parameters the secondary parameters like shape of the circumferential flux pattern and its spread are also considered. These parameters are then used in the classifier module to finally predict the defect feature dimensions namely length, width and depth. Use of secondary parameters in addition to primary for characterization of defects from MFL signal has been reported in [4]. However, the correlation of these parameters with defect size is obtained by neural nets. An attempt has been made in the present paper to correlate the secondary parameter to the nature

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of flux leakage such that a direct connection is visible with the defect sizing. Although both axial and radial MFL signals are used for defect characterization, not many references could be found in public domain discussing the empirical rules exclusively for spatially bipolar radial MFL signal. Although use of neural network has been reported for classification of complex defects [3–6], empirical rules prove to be a simple and useful solution of the standard characterization problem. This paper discusses the structure of empirical relationships used by the classifier module for length, width and depth sizing of metal loss defects from the radial MFL signal. For most of the naturally occurring corrosion defects, the signal to noise ratio (SNR) of radial MFL signal is higher than its axial counterpart. Moreover, the spatial interval between negative and positive peak of the bipolar radial flux is a direct and accurate indication of the length of the defect. The structure of the formulae is derived from the first principle, but the parameters in the empirical relationships have been estimated from experiments with known defects. Solution of parameter estimation problem given the structure is obtained by minimizing error in sizing, based on a chosen criterion such as that of least squares. The topic is not discussed in this paper to limit the length of the paper. The empirical rules have been validated by interpreting data from actual trials.

The paper demonstrates the results of feature and defect analysis based on radial MFL signals that have been verified by dig site inspections. The final aim of the analysis is to predict the safe maximum operating pressure (MAOP) for the pipeline. The MAOP is estimated as per standards (*e.g.* ASME B31 G) based on the assessment of defect features.

Rest of the paper is structured as follows. Section 2 gives an overview of MFL data processing including data de-noising and feature extraction. Section 3 discusses the method of defect characterization and sizing. Section 4 discusses the results obtained by applying these techniques on data sets recorded from actual runs in buried pipelines. Section 5 concludes the paper indicating major achievements and discusses further scope of work in this field.

2. An overview of data processing

Although MFL data is analyzed offline, on-line data processing is necessary for reducing the size of the data. Handling and storage of large volume of data from a run of several hundred kilometers become cumbersome and costly. Usually a large volume of MFL signal from a run does not contain any information. Hence, we need to save only those parts of the signal that contain information about pipe feature or metal loss defects. This requires taking a decision, on-line, regarding usefulness of the data. The same is achieved by checking for the presence of information above a threshold in wavelet-decomposed signal.

The offline data processing involves locating pipe features and defects, extraction of signal features at the defect locations, characterization or sizing, classifying a defect as per standards and reporting significant defects. Consistency check of signal features in the report calls for compensation/correction of features and rejection of spurious indications due to sensor bounce, etc.

Characterization of metal loss defects involves accurate sizing and profiling of the defects from MFL signals. The primary parameters that significantly affect the distribution of leakage flux density near a defect are percentage wall loss (%WL), length (dimension of a defect along the direction of magnetization) and width (dimension of a defect perpendicular to the direction of magnetization). A more detailed discussion on the subject is available in [2,4,7–9].

2.1. Pre-processing of raw data

In offline processing, the raw MFL data from a run is first scanned for preliminary information on the quality, continuity, environment (ambient temperature, vibration level, etc.) and duration of data stored to ascertain the health of the run. It also involves correcting signals with reference to calibration measurements carried out for the sensors with the instrument prior to the run. This calibration run involves normalizing sensor response from the data collected on a full periphery groove of uniform wall loss.

2.1.1. De-noising with undecimated discrete wavelet transforms

The undecimated DWT is a linear bounded operator W consisting of J+1 linear operator

$$W_j : l^2(Z) \to l^2(Z), \quad j = 1,2,\ldots,J+1 \tag{1}$$

In wavelet literature j is referred to as scale, as an alternative to frequency. One can compute DWT of the discrete signal $x[n]$ with a low-pass filter (h) and a high-pass filter (g). Filters h and g are finite impulse response (FIR) filters. The resulting sequence of discrete signals is called the undecimated DWT of the sequence $x[n]$. The operators W_j, for undecimated dyadic DWT, are the convolution operators. The reconstruction operator W^{-1}, an inverse of W, can also be implemented by non-sub-sampled octave band filter banks.

The perfect reconstruction relationship for undecimated filter bank is similar to that for decimated filter bank and FIR filter coefficients, odd length and symmetric, derived for decimated implementation can also be used in undecimated case, normalizing each coefficient by $\sqrt{2}$ [10]. This allows us to test signals with the family of readily available, so-called bi-orthogonal spline wavelets, in our work. The impulse responses of the filters used in this work are either symmetric or anti-symmetric.

2.1.2. De-noising using soft thresholding of signal in wavelet domain

Optimum solution for de-noising by better approximation is obtained by taking penalized least square approach [11]. The original signal is first decomposed using DWT and then insignificant coefficients at each scale are zeroed by the thresholding operation. Soft thresholding reduces significant DWT coefficients by the threshold amount and cuts off the coefficients lower than the threshold. The idea is that the noise is present not only in a particular band of frequency but also at all frequencies and it can be removed by amplitude thresholding. Soft thresholding can be described as

$$\begin{aligned} x[n,\theta] &= x[n]-\theta \text{ if } |x[n]| > \theta \\ x[n,\theta] &= 0 \text{ if } |x[n]| \le \theta \end{aligned} \tag{2}$$

Level of threshold $\boldsymbol{\theta}$ is chosen by estimating median absolute deviation of DWT coefficients at the finest scale. It is assumed that the finest scale mainly comprises of noise. Inverse DWT recovers the desired de-noised signal. A strategy is formulated to change the level of threshold at different scales. One can also reject the DWT coefficients at some scales if all the coefficients at those scales are considered to be noise and recombine only those scales that have relevant data above threshold.

The signal could be de-noised further by using more compact representation such as wavelet modulus maxima representation (WMMR) or wavelet maximum curvature point representation (WMCPR) [10,12]. It is possible to estimate signal features from the multi-scale evolution of modulus maxima as the