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APPLICATION OF MULTIRESOLUTION ANALYSIS AND DEEP LEARNING TO OBTAIN FAILURE PRESSURE OF CORRODED PIPELINES

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Abstract. The assessment of corroded pipelines is considered a very important task in the oil and gas industry. The present work aims to develop an efficient system to accurately predict the burst pressure of corroded pipelines with complex corrosion profiles through hybrid models using multiresolution analysis, numerical analysis, and metamodels. The corrosion profile is obtained from ultrasonic inspections and the data is provided as a river bottom profile. The real corrosion shapes are parametrized considering a discrete wavelet transform to reduce the amount of data that describes the defect. The coefficients obtained from the wavelet transform are used as inputs to feed a deep neural network system for quickly and accurately predict the burst pipeline pressure. Eight different steel materials are considered in the NN build process. Synthetic models that have similar statistics to real corrosion profiles are created and submitted to non-linear FEM analysis, for the different materials. The failure pressures obtained from the synthetic defects are used to train a neural network to predict the burst pressure of the pipelines. The results obtained with the deep neural networks are very accurate for all cases presented in this work.

1 INTRODUCTION

One of the most important causes of failure and incidents in pipelines is corrosion. Due to the severe consequences and impact in several areas such as social, economic, and environment the pipelines have to be continuously monitored. The possibilities for pipelines assessment are inspection, standards, and numerical simulations.

It is well known from literature that calculations based on standards in general simple, fast, commonly presents very conservative results. In the other hand, the finite element method has been successfully used to predict the failure pressure [1-3] and it is also used here.

The ultrasonic technology inline inspection (UT-ILI) can provide data such as a river-bottom profile (RBP), that is a detailed two-dimensional representation of the remaining wall thickness along the pipeline. These projections are formed by the minimum values across the circumferential width. With this data we can determine the shape of corrosion formed by circumferential peak depths and the total length of the defect. As a consequence, failure pressure can be obtained through simulation with 2D FE analysis [4]. However, the number of thickness measurement in a RBP can be very large which is an issue to generate the required models for analysis. To overcome that, multiresolution analysis (MR) [5] is used in this work to parametrize and to reduce the size of data necessary to represent the geometry of the defect.

Moreover, to obtain fast results a deep neural network (NN) [6] is built. For that, synthetic corrosion profiles with same statistical properties of real corrosion defects are modelled and used to compute the failure pressure by 2D FE. The coefficients of decomposition using wavelet transform [7,8] and the obtained failure pressures feed the NN and after be trained this will be tested for real corrosion profiles.

Comparisons with experimental, semi-empirical and 3D FE were performed and good agreement are obtained with de 2D simulations based on the models from MR analysis. This validation study considered API 5L-X80 steel which is the material from the real corroded pipelines used to build the RBP models. Next to the validation step, the NN will also be trained for all class of API 5L stell materials. The results obtained for all cases considered were very satisfactory.

2 FINITE ELEMENT MODEL

Through a file containing the main remaining thicknesses of the corroded pipeline, all defects are assembled to build the RBP model as illustrated in Figure 1. The configuration represented in this figure shows that, at each longitudinal distance, a scan of the remaining thicknesses is performed in the circumferential direction, using the smallest thickness of the pipeline wall to create the River-Bottom profile. In this work, the RBP is created using spline curves to avoid stress concentration at each point created in the profile. After obtaining the profile, the finite element mesh is generated using 4 elements in the wall thickness in the region of the defect and a transition region from 4 to 2 elements in the farthest part of the defect. A typical mesh discretization for a RBP can be seen in Figure 2.

The Axisymmetric FE formulation [9] allows the use of 2D generated model to carried out the RBP analysis. For that, a cylindrical coordinate system is used, the loads and boundary conditions (BCs) are applied and the analysis file is created. This file contains the main information of the FE model such as the nodal coordinates, connectivities of the elements, element type, material properties, boundary and load conditions. The material properties are represented here by a multilinear stress-strain relation [4].

Nodal displacement restrictions are imposed in the *z* direction (longitudinal) of the pipe ends and load conditions refers to the internal pressure, which are applied directly on the inner edges of the pipeline. Both conditions are indicated in Figure 3.

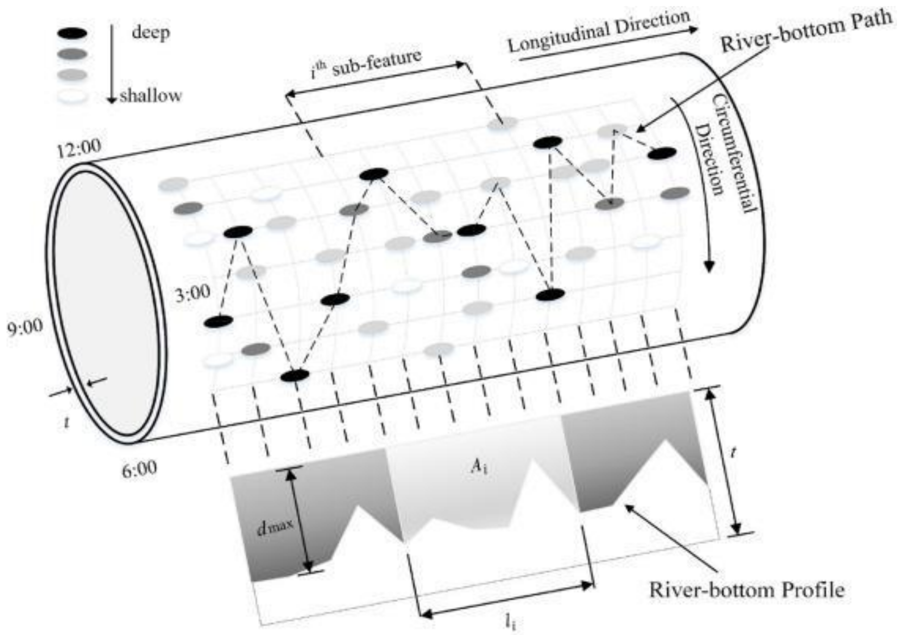

Figure 1: Representation of obtaining the RBP

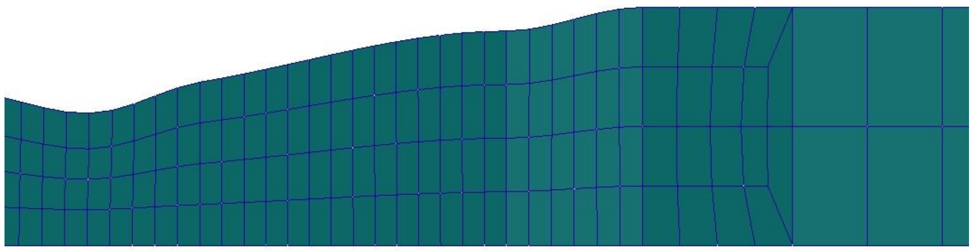

Figure 2: FE mesh and transition region

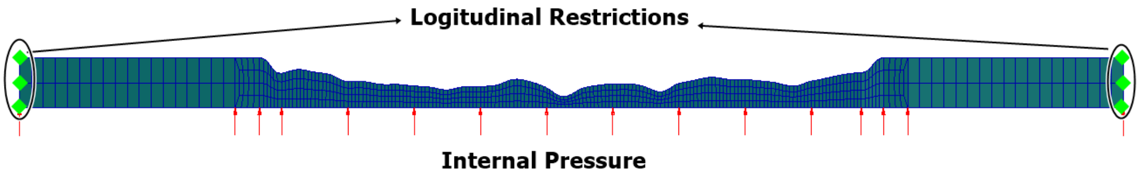

Figure 3: BCs and loads conditions

To predict the burst pressure in pipes with a complex corrosion profile, a large amount of data is needed to provide all the information that the neural network needs to learn and generate an adequate predictive capacity. In this work, synthetic models are generated to be training data sets and validation data sets for the neural network. In total, around 9;612 synthetic cases are generated associated with a specific material property. As eight materials are considered this represents 76,896 cases to be run. The failure pressures of these cases are used as input parameters to the deep neural network. The models are randomly generated by statistical fitting of each corrosion profile [10].

3 FAILURE CRITERIA

The failure pressure of corroded pipelines subjected to internal pressure can be estimated by non-linear simulations using the FEM and an appropriate criterion of failure previously validated. In this work, both geometrical and physical nonlinearities are considered in the numerical simulations. The physical non-linearity is characterized by an elastoplastic constitutive law with isotropic hardening in large deformations. The non-linear analyses will be performed by *Code Aster* software [11].

Here, the failure pressure for the pipeline is defined as the pressure when the von Mises equivalent stress at any point in the corrosion area reaches the true ultimate stress of the material [2,3].

4 WAVELET DECOMPOSITION

As mention, wavelet transforms [7, 8] are used here to parametrize the remaining thickness of corroded pipelines and the wavelet coefficients are used as input data to a NN code for fast prediction of pipeline's burst pressure. This is necessary to reduce the amount of geometry data for each defect, which can be in the order of tens of thousands of points.

To find the best decomposition to apply to the analysis of corroded pipelines, several wavelet families (biorthogonal, Coiflet, Daubechies, Meyer, Haar and reverse biorthogonal) were tested, varying for each one the number of vanishing moments and the number of taps (or length of the wavelet). The shape of the wavelet functions and scaling functions tested can be seen in [10]. From the studies conducted here, the best wavelet was the reverse biorthogonal, with 3 vanishing moments. Twelve real river bottom profiles obtained using ILI inspection are used to generate the synthetic models. Figure 4 shows one of them.

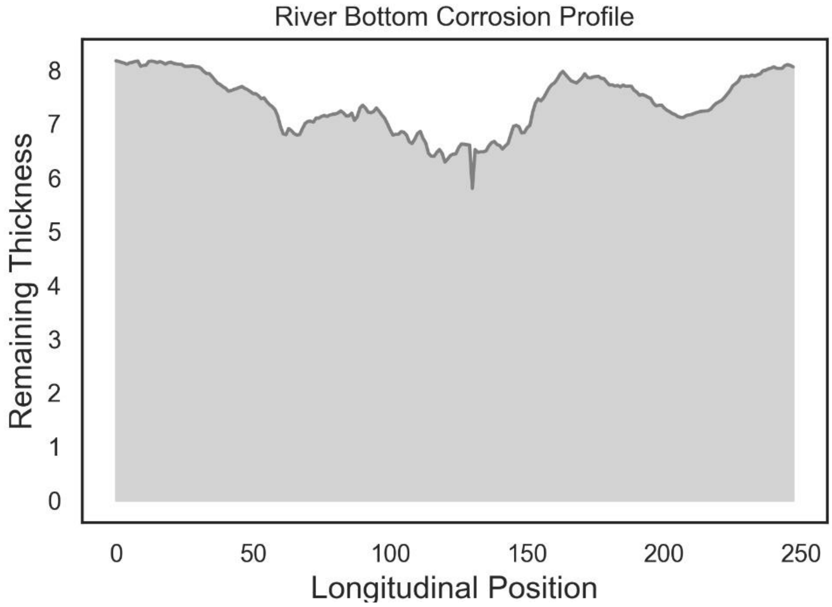

Figure 4: Example of a real river bottom profile.

To illustrate the process, in Figure 5 the decomposition applied to case 4, using reverse biorthogonal wavelet family with 3 vanishing moments in all levels is shown. The left column shows the approximation coefficients and the right column shows the detail coefficients.

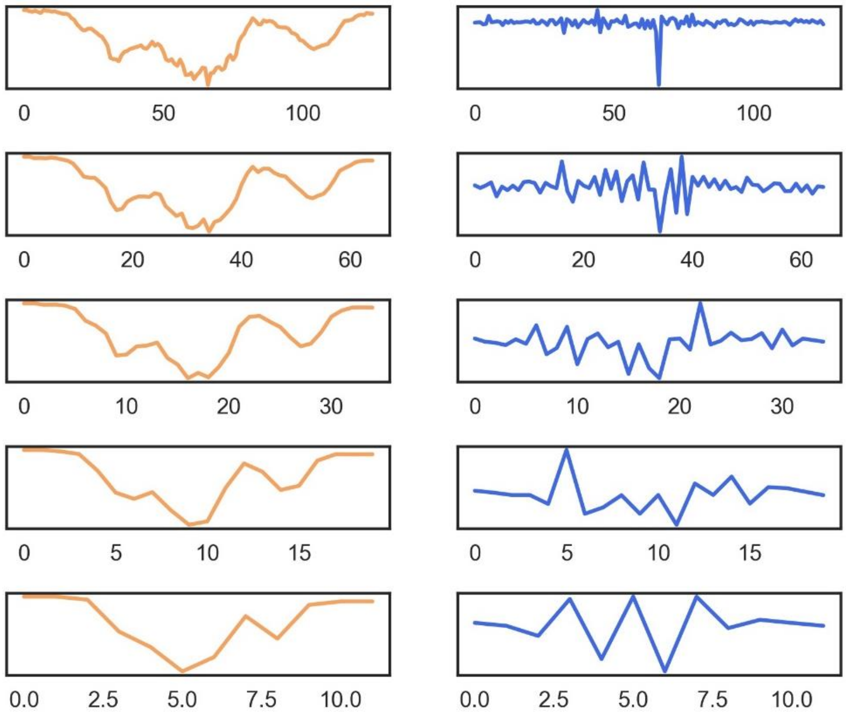

Figure 5: Reverse Biorthogonal decomposition with 3 vanishing moments

The coefficients can be used as a low pass filter and as a high pass filter. To reduce data, the detail coefficients (high pass filter) are set to zero. Figure 6 shows the original and filtered data after signal reconstruction using Reverse Biorthogonal decomposition until Level 5.

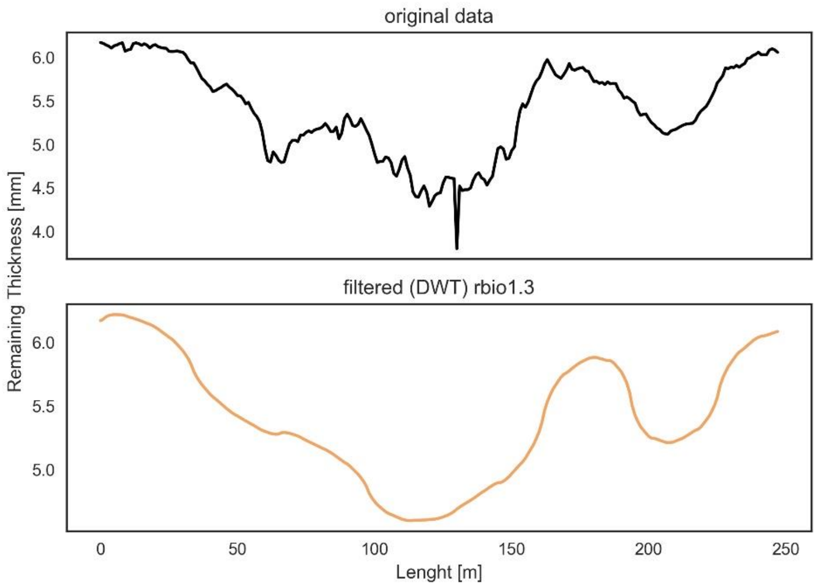

Figure 6: Original and filtered case using Reverse Biorthogonal

5 ARTIFICIAL INTELIGENCE

A deep neural network (DNN) is considered here. This is an artificial neural network with many layers between the input and output layer [6]. Different options to solve the optimization problem, can be used. The backpropagation algorithm [12] efficiently computes the gradient of the loss function concerning to the weights and biases of the artificial neurons. Deep Neural Networks can predict solutions with high accuracy in many research fields and it is used here for pipeline safety assessment. A free and open-source library, TensorFlow [13], is used in the present work.

As already mentioned, input parameters are the approximation coefficients, obtained after wavelet decomposition. Other input data are: the dimensionless parameter (*dp*) shown in Eq. (1), ultimate stress, yield stress and ultimate strain and the failure pressure obtained from the non-linear analysis by MEF.

$$dp = \frac{L}{\sqrt{De \times t}} \tag{1}$$

In above equation, *De* is the outside diameter of the pipeline, *t* is the nominal thickness and *L* is the length of corrosion defect. The dimensionless parameter (*dp*) is used by codes and standards to indicate how long is the corrosion defect. In the input layer of the neural network, the number of neurons was set as

$$\max(ncoeffs) + nmat + 1 \tag{2}$$

where *ncoeffs* results from the MR decomposition (for the selected wavelet = 18), *nmats* is equal to three (material parameters: ultimate stress, yield stress and ultimate strain). In the present application the summation of Eq. (2), equals to 22.

After a series of tests, the number of hidden layers was set to five, and the number of neurons in the hidden layers was set equal to the number of input neurons.

The output layer has one neuron. Therefore, the neural network was composed by one input layer, five hidden layers, and one output layer. The activation function was the Sigmoid [6] and the optimization algorithm used is the Adaptive Subgradient Methods (Adagrad) [14].

6.RESULTS

6.1 RBP models validation

Deterministic solutions were extensively validated in [4]. There, a convergence study to select the best element and mesh density for the RBP models was firstly carried out. A mesh convergence study was performed for bilinear quadrilateral and quadratic quadrilateral elements, using different number of elements along the defect thickness. From this study it was observed that the specimens analyzed remained with almost constant failure pressure for the different mesh density variation and type of element tested. Due to this reason, the bilinear element with 4 elements along the thickness was chosen to perform the FE analyses, due to the shortest analysis time and memory consumption which were significantly smaller than those required to the other configurations.

Next, the chosen FE configuration for the RBP model was used for failure prediction comparison of four specimens provided in literature [15]. The results were compared with 3D FE simulation, experimental analysis and semi-empirical methods. For the specimens analyzed, the quality of the proposed methodology was attested by an average deviation of about 3% from experimental results. Also, it is less conservative than the results based on the methodologies described in the standards.

6.2 MR models validation

In [10] one hundred and six wavelet decomposition were performed for each of the twelve river bottom cases, providing 1,272 models for a specific API X80 material. Axisymmetric finite element models were generated and submitted to non-linear FEM analysis. The failure pressure computed with finite element models generated from the geometry reconstructed with each wavelet family was compared to the failure pressure computed with finite element models built from the original defect geometry for all the twelve models.

Relative difference between the failure pressures computed with the wavelet filtered geometry and the original geometries were calculated. It was observed that data reduction has been successfully achieved, without significant loss of accuracy.

6.3 NN case studies

To train the DNN several parameters need to be set. Only the synthetic data is used to train and validate the network. The proportion was set to 70% and 30% respectively. The size of batches to return is set to 100 and the number of epochs to iterate over data is set to 3;000.

The failure pressures ($\overline{Y_i}$) are predicted at the test set. Comparisons are done with the given failure pressure (Y_i) at the test set and the Mean Absolute Percentage Error (MAPE), is calculated as in Eq. (3). MAPE calculated between them was 2.72%, that is a very accurate value. Next, the trained DNN is used to predict the failure pressure of real river-bottom profile defects. With the results of burst pressure by MEF and the predicted results obtained from the neural network, MAPE equals to 2.85%. The R2 score [16] was 0.99. These computations involved all investigated materials (8).

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\overline{Y_i}-Y_i}{Y_i}\right| \tag{3}$$

Figure 7 shows the performance of the obtained NN for the eight different investigated materials and the twelve river bottom profiles. The FE solution is the straight red line. The predicted NN calculations over 96 (12 profiles x 8 materials) cases are indicated in dots. As can been seen a very good comparison is obtained. It is worth to mention that a single estimation by the built NN took around 1e-6 seconds. Which means 99.9% in computational savings compared to a FE based solution (RBP and 3D FE models).

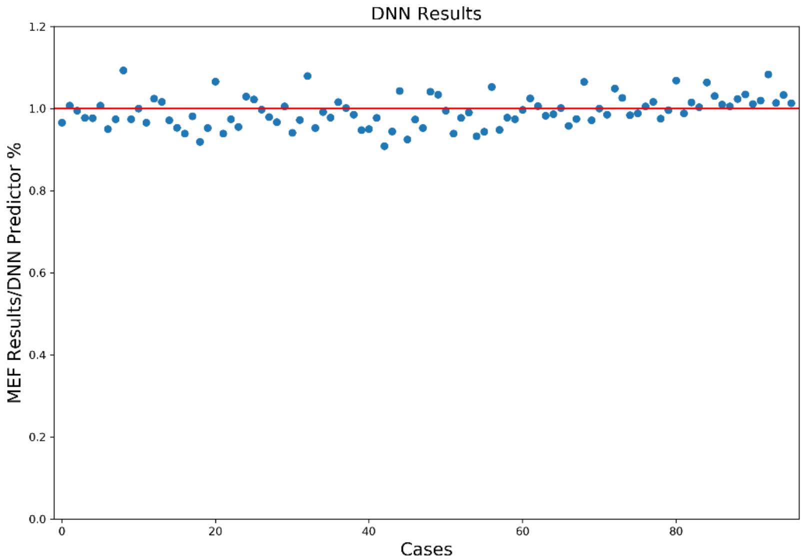

Figure 7: Comparison between failure pressure calculated using MEF and DNN prediction.

7 CONCLUSIONS

In this work, the failure pressure of corroded pipelines has been predicted by a hybrid model using multiresolution analysis, numerical analysis and metamodels. Synthetic corrosion profiles preserving the statistical properties of 12 real corrosion defects were created and used to estimate the failure pressure in each one of them by Finite Element Analysis (FEA). A total of 76.896 (801synthetic x 12 RBP x 8 materials) cases have been simulated. The work also addresses the parametrization of real corrosion shapes and the use of its coefficients as input to a neural network system that can predict the burst pressure accurately and quickly. The MR coefficients together with the material properties and failure pressure are the input values used to construct the NN model.

The main conclusions of this study are:

- The MR decomposition was fundamental to generate a large number of models necessary to create an accurate Deep Neural Network.
- The coefficients of the MR together with the material properties and assessment of the pipelines fed and efficiently trained the NN.
- The created NN was able to accurately predict the failure pressure with insignificant computational time.

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