Development of a computational tool for immediate assessment of the structural integrity of corroded pipelines

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Abstract. Pipelines are one of the safest ways to transport hydrocarbons however this type of transport is subjected to severe damage that can be associated, mainly, with corrosion. Therefore, the structural integrity assessment of corroded pipelines is of great importance for the oil and gas industry. For the prediction of the failure pressure of pipelines with corrosion, semi-empirical and numerical methods are commonly used. Semi-empirical equations are computationally inexpensive, but, in general, lead to more conservative results. On the other hand, the finite element method (FEM) is more accurate and presents less conservative responses, but it is more expensive. In this work, a system developed with a low computational cost equivalent to semi-empirical methods, but with more accurate results will be presented. For this, a set of models, previously defined, that have a single idealized defect, dimensions, and the material curve, were evaluated through the FEM and the results, together with the model data, were stored in a database, where they can be accessed remotely via an API. These data can be used to estimate the failure pressure of any new model. The obtained results were validated against experimental test results found in the literature, finite element analysis, and semi-empirical models.

Keywords: Pipeline corrosion assessment method, finite element analysis, remote database, API

1 Introduction

Corrosion in steel pipelines is a problem in the hydrocarbon industry, as it affects their structural integrity, which leads to a reduction in the strength of the pipe and, if not properly monitored, can cause an accident (Ren et al. [1]). In order to reduce these risks, there are several ways to assess the structural integrity of the pipeline, among them there are semi-empirical and numerical methods.

Semi-empirical methods have a low computational cost, but often present conservative results, because of this, such methods can generate unnecessary costs by prematurely replacing a section of pipeline and stopping a line to carry out the replacement. Numerical methods, on the other hand, have greater accuracy, but are much more computationally costly, which requiring more time to obtain a result for the failure pressure, which can increase the risk of maintaining an active pipeline section (Kumar et al. [2]).

In this article, a new tool that allows alternative approaches for evaluating the structural integrity of corroded pipelines will be presented. The tool is composed of a database, where the results of analyzes previously run via the finite element method are stored, and an Application Programming Interface, API, provides access to analysis data stored in the database.

Our goal is to provide data that can be used for failure prediction using methods that are computationally cheaper than numerical methods, which provide a computational time response equivalent to semi-empirical methods and with greater accuracy and less conservative results. Thus, an application of the tool for the construction of substitute models will be presented and two other approaches using interpolation.

2 Methodology

2.1 API

For the development of the tool, the Flask microframework was used due to its robustness, simplicity, and speed (Ronacher [3]). For the interactions with the database, the SQLAlchemy library was used, which provides an interface with the database that abstracts the need for further configurations to deal with queries, providing the main commands (Bayer [4]).

The architecture used in the development of the server was REST, since the system will work with a client-server structure, with a uniform interface and without the need for states (Richardson et al. [5]). The data return format is JSON, due to its wide use among applications, the ease of handling the data, the wide support for the format in several programming languages, and the support in the Python standard library (Pezoa et al. [6], Van Rossum and Drake [7]).

The database is relational, it was fed with results of non-linear analyzes via the finite element method performed using the open code program code_aster (de France [8]). Analyzes of pipe models with simple defects were performed, with the longitudinal defect length (L_{defect}), circumferential defect width (w), defect depth (d), the outside diameter of the duct (OD), the thickness of the duct wall (t), the length of the model (L_{pipe}) and the steel used. This information is presented in Table 1.

As in Ferreira et al. [9], the equivalent von Mises stress at any point in the corroded area being equal to the ultimate stress of the material. To generate the curve of the materials used in the analyzes, the Ramberg-Osgood relationship (Ramberg and Osgood [10]), that can be expressed by eq. 1, was used, providing data regarding the flow and rupture of the material, as seen in the Fig. 1.

$$\epsilon = \frac{\sigma}{E} + \alpha \frac{\sigma}{E} \left(\frac{\sigma}{\sigma_y} \right)^n . \tag{1}$$

Where n and α are hardening coefficients that depend on the material being considered and its hardening behaviour. E is the Young's modulus, σ_y is the yield strength, with the true ultimate tensile stress (σ_u), and true ultimate strain (ϵ_u) the hardening coefficients are calculated and the others points in the curve are found (Ferreira et al. [9]).

Table 1. Models Parameters

Input Parameters	Unit	Value(s)
OD	mm	458
t	mm	8.2
w	mm	100, 200, 300, 400, 500, 600, 700, 800, 900, 1000
L_{defect}	mm	100, 200, 300, 400, 500, 600, 700, 800, 900, 1000
d	%	20, 30, 40, 50, 60, 70, 80
L_{pipe}	mm	$10OD + L_{defect}$
Material	-	API 5L X42
	-	API 5L X46
	-	API 5L X52
	-	API 5L X56
	-	API 5L X60
	-	API 5L X65
	-	API 5L X70
	-	API 5L X80
Defect location (surface)	-	Internal
	-	External

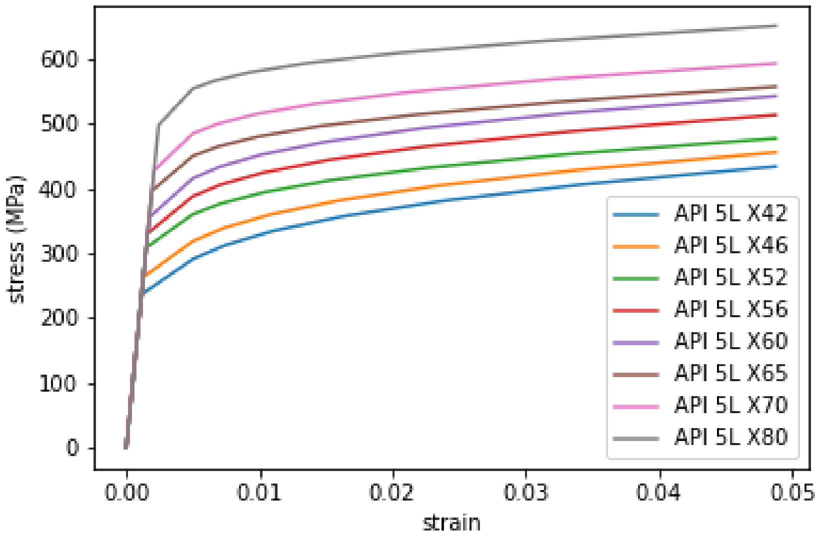

Figure 1. Material curves, true stress x true strain

Some of the intended uses for this data are interpolation directly through the data contained in the database, such as multi-linear interpolation or some other data interpolation function. In addition, the data can be used to generate surrogate models in the case of more complex analyzes, such as reliability analysis. In the following sub-sections, some approaches are presented and detailed.

2.2 Interpolation

Interpolation was used in two approaches, the first one is the multi-linear interpolation. The data were divided into sets by steel and surface where the defects are located. Then, the following data from each model were grouped $(L_{defect}, w, d, P_{FE})$, forming a 4-tuple. The 4-tuples close to the point of interest are selected and a multi-linear interpolation is performed.

The second approach was locally using the radial basis function (RBF) method (Elsayed et al. [15], Keane et al. [13]). With the point of interest in hand, a search is made for the 4 smallest Euclidean distances between the point and the 3-tuple formed by (L_{defect}, w, d), with these data and knowing the pressures in advance of failure pressure in these four 3-tuples creates a new response surface that is used to estimate the failure pressure of the model of interest.

2.3 Surrogate model

The last approach was using surrogate model, and RBF method (Elsayed et al. [15], Keane et al. [13]) on the material curve and defect surface sets. First, sampling was made for each set using the latin hypercube sampling method (Romero et al. [12]), so that the points are well distributed over the data set. With the sampled points, the response surfaces were created using the RBF.

Sampling plan

The big challenge in this type of approach is to generate a replacement model that is as reliable as possible and using the least number of high-fidelity model analyzes. Thus, it is necessary to sample the points where the high-fidelity models will be evaluated. The first step in building a surrogate model based on data fit is to generate a sample of points. These are places in the design space where the response values of the high-fidelity models will be calculated to build the approximate model. The selection of the sample is a very important step, since, for cases where the evaluation of the function involves a high computational cost, an effective sampling plan must be sought, which means a minimum number of points that will guarantee a good replacement model precision (Pinto

[11]). Due to the tool presented here, this cost is reduced to a database query.

In this work, Latin hypercube sampling (LHS) is used, as in general, through this technique, a better uniform distribution of points is obtained. This is due to the greater regularity in individual sampling in each dimension of the function parameters before the parameters are randomly combined to generate the set that will define the coordinates of the sample points (Romero et al. [12]).

Latin hypercube sampling

To obtain an LHS sample, the interval of each dimension of the sampling space is divided into subintervals, which do not overlap, of equal probability. For a project domain with dimension n, this partitioning results in a total of m^n subranges in the project domain, where m is the total number of points in the sample. These m points are randomly selected in the design domain obeying the following restrictions: each point must be randomly allocated within a subinterval of the domain and for each one-dimensional projection of this point there will only be one and only one point in each subinterval (Pinto [11]).

In possession of the sample points, prediction expressions are developed to evaluate the function at non-evaluated points of the domain. In this work, the predictors are based on radial basis function (RBF) models (Keane et al. [13], Gutmann [14]).

2.4 Radial basis function

The radial basis functions method is a means of approximating multivariate functions in terms of the functions, known properties, and easier analysis (Elsayed et al. [15], Keane et al. [13]).

Let m pairs of different points $M = \{x_1, ..., x_m\} \subseteq R^n$ and answers $F = y_1, ..., y_2\ subseteqR$. We look for a radial basis function (RBF) $\hat{f}$ of the form (Gutmann [14]):

$$\hat{f}(x) = p(x) + \sum_{i=1}^{m} \lambda_i \phi(||x - x_i||),\ x \in R^n. \tag{2}$$

That interpolates the data $(x_1, y_1), ..., (x_m, y_m)$. Where x_i is the i-th of the n_c centers of the base functions and ϕ is a vector containing the values of the base functions themselves ϕ, evaluated in the distance Euclidean between a point x and the percent x_i of the base functions, $r = ||x - x_i||$. An RBF can be defined as a weighted sum of translations of a radially symmetric basic function, ϕ, augmented by a low-grade polynomial term, p.

2.5 Precision measure of the surrogate model

The response surface created by the RBF passes through all sampled points. However, to verify if the metamodel is adequate, additional points are used to assess the model's accuracy, this is done through the calculation of error measures. In this work, the Root Mean Square Error (RMSE) was used. The RMSE quantifies the amount of residual error between actual data and predictions at selected points (Keshtegar and Ben seghier [16]). Its expression is given by eq. 3

$$RMSE = \sqrt{\frac{\sum(P_{Pred} - P_{Exp})^2}{n}}. \tag{3}$$

Where P_{Pred} is the predicted pressure, P_{Exp} is the experimentally obtained burst pressure, and n is the number of cases analyzed.

3 Results

In order to validate the approaches presented in the previous session, analyzes were performed using the finite element method so that the results could be compared with the experimental failure pressures present in the literature. Five specimens available in Benjamin et al. [17], Andrade et al. [18] and Freire et al. [19] were analyzed, these specimens were selected because they have similar dimensions to the cases present in the database, and they are presented in Table 2. All finite element models have an outer diameter of 458mm, the wall thickness of 8.2mm, and use the material API 5L X80 steel. The equation used to calculate the percentage error is given by

$$\frac{P_{FE} - P_{Exp}}{P_{Exp}} 100\%. \tag{4}$$

Where P_{FE} is the pressure calculated by the finite element method, P_{Exp} is the rupture pressure obtained experimentally.

Table 2. Comparative results: experimental x FE

Specimen	OD	t	L_{defect} (mm)	w (mm)	d (mm)	P_{Exp} (MPa)	P_{FE} (MPa)	$Error_{P_{FE}}$ (%)
CDTS3	459	8.1	40.0	445.0	6.01	20.51	18.0	-12.24
RDTS1	459	8.1	208.0	32.1	2.36	22.73	21.0	-7.61
RDTS2	459	8.1	208.0	32.1	4.05	17.36	16.0	-7.83
IDTS8	457.2	7.93	40.05	32.0	3.75	24.2	24.0	-0.83
IDTS2	457.2	7.93	39.6	31.9	5.39	22.679	21.75	-4.09

After creating the surfaces using each of the approaches, 50 models of interest generated randomly were evaluated, and for comparison purposes, the results obtained through the B31G standard (Anon [20]) were also added. Error data are presented in Table 3. Figure 2 shows the results in a comparative way between the estimated value and the value calculated through finite elements.

Table 3. Comparative results

Method	RMSE
Multi-linear	2.05
RBF - Global	3.08
RBF - Local	1.07
B31G	3.77

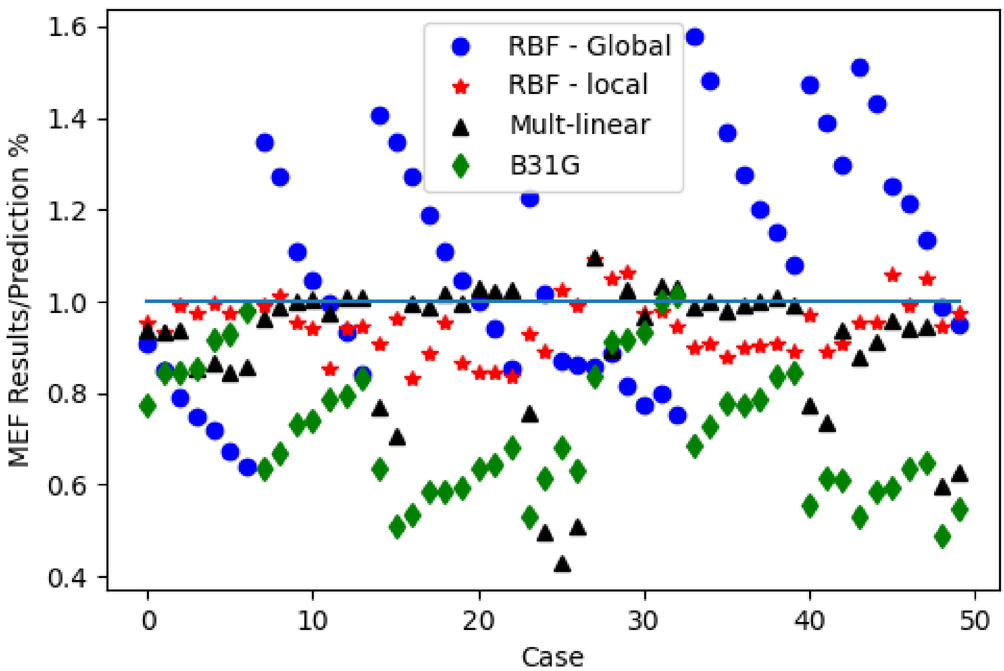

Figure 2. Comparison between failure pressure calculated using MEF and prediction methods

The approach using the RBF method locally returned the smallest error among the 3 methods used, with its results being in the range of 10% more and 20% less than the FE.

The approach using the multi-linear interpolation method presented, in general, results very close to those calculated via FE, but some points presented values up to 40% of the value calculated via FE. Despite making mistakes for safety, the value was much lower than that obtained through the FE.

The last approach was using the RBF method globally, which showed the greatest errors, with cases in which it estimated a failure pressure value of up to 60% of the estimated value through the FE. Overall, it still had a smaller error than the B31G standard.

4 Conclusions

The main objective of this paper was to present the tool that is being developed and some approaches that it allows. As a way to validate the results obtained, analyzes of 5 specimens presented in the literature were performed and the comparative errors between the experimental results and the numerical method were verified. Only 1 of the cases the error was greater than 10%, in all cases the error was down, in the sense of safety. After this validation, analysis of fifty randomly generated cases was performed, the finite element analysis of these cases was performed and then compared with the results obtained were through the interpolations of data from the tool presented were here.

As shown, the results considering obtained via the interpolation methods using the data provided by the tool had smaller errors than those obtained using the B31G standard.

The part with the highest computational cost for the creation of the response surface using the RBF method is the function evaluations at the sampling points. When using data from the database, it reduces the cost of analysing high-fidelity models for database queries of data.

Acknowledgements. The authors wish to thank PETROBRAS, FINEP, CAPES and CNPq for the financial support of various research projects developed in this area by the PADMEC Research Group.

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References

[1] L. Ren, T. Jiang, Z.-g. Jia, D.-S. Li, C.-l. Yuan, and H.-N. Li. Pipeline corrosion and leakage monitoring based on the distributed optical fiber sensing technology. *Measurement*, vol. 122, 2018.

[2] S. Kumar, S. Karuppanan, and M. Ovinis. Failure pressure prediction of high toughness pipeline with a single corrosion defect subjected to combined loadings using artificial neural network (ann). *Metals*, vol. 11, pp. 373, 2021.

[3] A. Ronacher. Flask, user's guide. USA: Trelgol Publishing. [Online; accessed 2021-08-06], 2021.

[4] M. Bayer. Sqlalchemy. In A. Brown and G. Wilson, eds, *The Architecture of Open Source Applications Volume II: Structure, Scale, and a Few More Fearless Hacks*. aosabook.org, 2012.

[5] L. Richardson, M. Amundsen, and S. Ruby. *RESTful Web APIs*. O'Reilly Media, Inc., 2013.

[6] F. Pezoa, J. L. Reutter, F. Suarez, M. Ugarte, and D. Vrgoč. Foundations of json schema. In *Proceedings of the 25th International Conference on World Wide Web*, pp. 263–273. International World Wide Web Conferences Steering Committee, 2016.

[7] G. Van Rossum and F. L. Drake. *Python 3 Reference Manual*. CreateSpace, Scotts Valley, CA, 2009.

[8] de E. France. Finite element $code\_aster$, analysis of structures and thermomechanics for studies and research. Open source on www.code-aster.org, 1989–2021.

[9] A. D. M. Ferreira, S. M. B. Afonso, R. B. Willmersdorf, and P. R. M. Lyra. Multiresolution analysis and deep learning for corroded pipeline failure assessment. *Advances in Engineering Software*, vol. , 2020.

[10] W. Ramberg and W. Osgood. Description of stress-strain curves by three parameters, 1943.

[11] J. W. O. Pinto. *Otimização Robusta do Controle de Poços de Reservatórios de Petróleo Utilizando Modelo Substituto*. PhD thesis, Universidade Federal de Pernambuco, PE, Brazil, 2020.

[12] V. Romero, J. Burkardt, M. Gunzburger, and J. Peterson. Comparison of pure and "latinized" centroidal voronoi tessellation against various other statistical sampling methods. *Reliability Engineering & System Safety*, vol. 91, pp. 1266–1280, 2006.

[13] A. Keane, A. Sóbester, and A. I. J. Forrester. *Engineering design via surrogate modelling: a practical guide*. John Wiley & Sons, 2008.

[14] H.-M. Gutmann. A radial basis function method for global optimization. *Journal of Global Optimization*, vol. 19, 2000.

[15] K. Elsayed, D. Vucinic, R. d'Ippolito, and C. Lacor. Comparison between rbf and kriging surrogates in design optimization of high dimensional problems, 2012.

[16] B. Keshtegar and M. Ben seghier. Modified response surface method basis harmony search to predict the burst pressure of corroded pipelines. *Engineering Failure Analysis*, vol. 89, 2018.

[17] A. Benjamin, J. Freire, R. Vieira, and E. Andrade. Burst tests on pipeline containing closely spaced corrosion defects, 2006.

[18] E. Q. Andrade, A. C. Benjamin, J. P. R. S.. Machado, L. C. Pereira, B. P. Jacob, E. G. Carneiro, J. N. C. Guerreiro, R. C. C. Silva, and J. D. B.. Noronha. Finite element modeling of the failure behavior of pipelines containing interacting corrosion defects. vol. Volume 4: Terry Jones Pipeline Technology; Ocean Space Utilization; CFD and VIV Symposium, pp. 315–325, 2006.

[19] J. Freire, A. Benjamin, R. Vieira, and J. Diniz. Burst strength of pipeline test specimens containing longitudinal or circumferential corrosion defects. *Conference Proceedings of the Society for Experimental Mechanics Series*, vol. 6, 2011.

[20] Anon. *ASME-B31G - Manual for Determining the Remaining Strength of Corroded Pipelines – A Supplement to ANSI/ASME B31 Code for Pressure Piping*. The American Society of Mechanical Engineers, New York, 1991.