Hindawi
Mathematical Problems in Engineering
Volume 2023, Article ID 4203541, 12 pages
https://doi.org/10.1155/2023/4203541

Research Article

A Methodology Based on 1D-CNN and Bootstrap Method to Estimate the Remaining Useful Life of Industrial Assets Suffering from Generalized Corrosion

M. H. Belonsi ,[1] A. M. G. de Lima,[2] M. A. V. Duarte,[2] R. N. Ferraresi,[2] and W. C. D. da Silva[3]

[1] *Campus Morrinhos, State University of Goiás, Morrinhos, GO, Brazil*
[2] *School of Mechanical Engineering, Campus Santa Mônica, Federal University of Uberlândia, Uberlândia, MG, Brazil*
[3] *Petrobras, Rio de Janeiro, Brazil*

Correspondence should be addressed to M. H. Belonsi; marcelo.belonsi@ueg.br

Received 17 May 2023; Revised 15 September 2023; Accepted 21 September 2023; Published 20 October 2023

Academic Editor: Junyong Zhou

The main goal of this work is to propose an efficient and accurate modern methodology to estimate the useful life of industrial assets used in oil and gas industry suffering from generalized corrosion. It merges the convolutional neural networks, extreme value theory, and bootstrap methods to handle the available corrosion data obtained through nondestructive inspection techniques for structural integrity assessments. It is due to the high cost of inspection techniques actually used in many industries to generate a reliable large amount of data to be analyzed by traditional statistical tools and technical factors, such as the inaccessibility of certain zones of the assets. First, the most appropriate extreme value distribution is determined to best fit the available inspection data, aiming to generate sufficient information for the training and testing processes of a one-dimensional convolutional neural network model to improve the accuracy of the useful life estimation. To demonstrate the main features and capabilities of the methodology, the dataset of AISI 1018 steel tubes of a heat exchanger used in a Brazilian refinery subjected to a general corrosion-type extreme process is retained herein. The results demonstrate that it is an interesting tool for inspection process to assist engineers and/or users in predictive maintenance phases to access the structural integrity of industrial assets subjected to extreme events such as general corrosion.

1. Introduction

Many industrial assets such as heat exchangers used in refineries and oil production units are frequently subjected to a variety of environmental and operational conditions that impact significantly their corrosion process and, consequently, their useful life. Thus, it is observed an increased demand for the development of more accurate and efficient statistical tools to analyze the corrosion data for structural integrity assessments. For example, Lemos et al. [1] have used the generalized Pareto distribution (GPD) with the peak-over-threshold (POT) and the first-order reliability method (FORM) to predict the remaining useful life (RUL) of heat exchangers used in Brazilian refineries. Tan [2] has applied the block maxima (BM) and POT to estimate the defect depth for uninspected areas of piping dead legs and the future growth of the defects. Shibata [3] has used the extreme value analysis (EVA) to predict the pit depth in an oil tank. In the same way, Kasai et al. [4] have proposed a method to assess the structural integrity of bottom floors of storage tanks using the EVA method. The same strategy has been applied by the Melo et al. [5] in study the internal pite corrosion in pipelines. Other interesting practical applications of EVA can be found in a study by Yamamoto and Shibata [6] and McNeil [7].

In the quest for corrosion process in industrial assets used in oil and gas industry, a comprehensive review of it can be found in a study by Popoola et al. [8]. Mohd et al. [9] and Bai et al. [10] have studied the generalized corrosion in subsea pipelines using traditional statistical tools to construct a nonlinear model to characterize the corrosion rate. In particular, Mohd et al. [9] have developed an empirical model

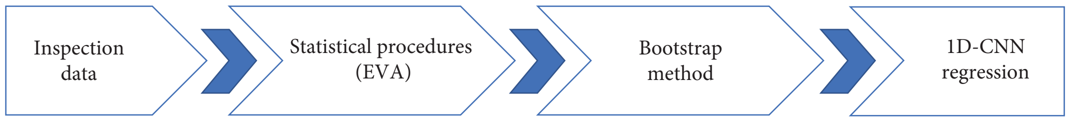

Figure 1: Illustration of the connection between EVA, bootstrap, and 1D-CNN network.

for the corrosion rate occurred in well pipes using the available information obtained by inspection for a period of time. After analyzing a number of well-known probability distributions to characterize the corrosion data, the authors have concluded that the Weibull function is the most adequate distribution for the corrosion process occurred in these types of systems. The study proposed by Ossai [11] suggests the use of a Monte Carlo simulation (MCS) in conjunction with a degradation model to estimate the possible failures of petroleum and gas pipelines. Zangenehmadar and Moselhi [12] have applied an artificial neural network (ANN) to predict the thickness' loss of steel tubes subjected to generalized corrosion. Le Son et al. [13] and Le Son et al. [14] have developed stochastic degradation models for a gamma degradation process to assess the RUL. Gong and Zhou [15] have used the FORM method to access the time-dependent reliability index of a pressurized segment of a pipeline having multiple active corrosion defects. They have adopted a linear model for the corrosion rate.

Hence, due to the current developments in the computer-aided and statistical tools combined with inspection technologies, the corrosion data obtained by nondestructive testing (NDT) such as Internal Rotating Inspection System (IRIS), eddy currents (EC), and remote field (RF) [1, 16] can be used for structural integrity analyses of various industrial assets. However, in practice, the integrity analyses of industrial assets using traditional approaches do not lead to accurate results in terms of RUL predictions, since the inspection data contain a limited number of corrosion data, especially for the heat exchangers used in oil and gas industry. It is due to the high cost of inspection techniques required to generate a reliable large amount of inspection data and technical factors such as the inaccessibility of certain zones of the assets. Consequently, it is observed a lack of reliable histories of inspection data to use traditional statistical tools to characterize the corrosion rate of such systems to be used to estimate their RUL with accuracy.

Therefore, modern methodologies based on artificial intelligence (AI) emerge as an interesting strategy to predict the RUL of industrial assets suffering from corrosion with reasonable accuracy. Clearly, in this field, it is still a challenge that has motivated this study.

At this time, it is important to recall the works by Mohd et al. [9], Zhao et al. [17], and Yamamoto et al. [18] regarding the determination of the most adequate distribution functions to characterize the corrosion process occurred by many industrial assets. In fact, the results by Mohd et al. [9] have demonstrated that the Weibull function is the most adequate probability distribution for modeling the generalized corrosion observed in gas pipelines. Thus, based on it and according to the previous study by Lemos et al. [1], the Weibull function will be used in this work to generate sufficient information for the training and testing of a neural network.

In summary, in oil and gas industries, corrosion data are typically obtained through NDT techniques, usually available in technical maintenance reports. For heat exchanger systems frequently used in refineries, these data are formed by remaining wall thicknesses of AISI 1018 carbon steel tubes. However, due to the lack of sufficiently representative inspection histories, it is not an easy task to extract the meaningful information of these data to characterize the corrosion rate and to estimate the RUL of the system.

In the literature, it can be found a few works dealing with the application of traditional statistical tools making use of run-to-failure or time-to-failure approaches [19–22] for structural integrity assessments. However, few works have used AI approaches to access the structural integrity of heat exchangers tubes used in oil and gas industry subjected to corrosion. Thus, it is used herein a one-dimensional convolutional neural network (1D-CNN) model with the EVA and bootstrap methods [23] to estimate the minimum wall thicknesses of the heat exchangers tubes and the corresponding RUL. It's worth mentioning that EVA methods play an important role in determining and estimating the most adequate nonlinear probability distribution used in data subsampling via bootstrap method. Figure 1 shows correlation between the described procedures. Details of the entire process can be found in Section 3.

2. Background on CNN Model

The CNN models have been used successfully in image processing and machine learning operations [24, 25], where the input data are normally in 2D format. In the case in which the input data are in 1D format, the CNN approach used must be also in 1D format [26, 27], being very attractive for dealing with the corrosion data of the heat exchangers addressed herein, which is formed by the remaining wall thicknesses of their steel tubes, as discussed in previous section.

According to a study by Coppe et al. [21], the CNNs are used for the abstract resources learning, alternating and stacking convolutional layers, where several filters are applied to extract the most significant spatial features of the data, and the grouping operations are responsible for choosing the significant information features [28]. More recently, the grouping layers are continuous replaced by fractionally and strided convolutions to keep the most useful information from resource maps, as discussed in a study by Coppe et al. [21]. The 1D-CNN approach retained in this study is summarized below.

Consider a vector, $x = [x_1, x_2, \ldots, x_n]$, with n data that characterize the state of corrosion in a certain operating time,

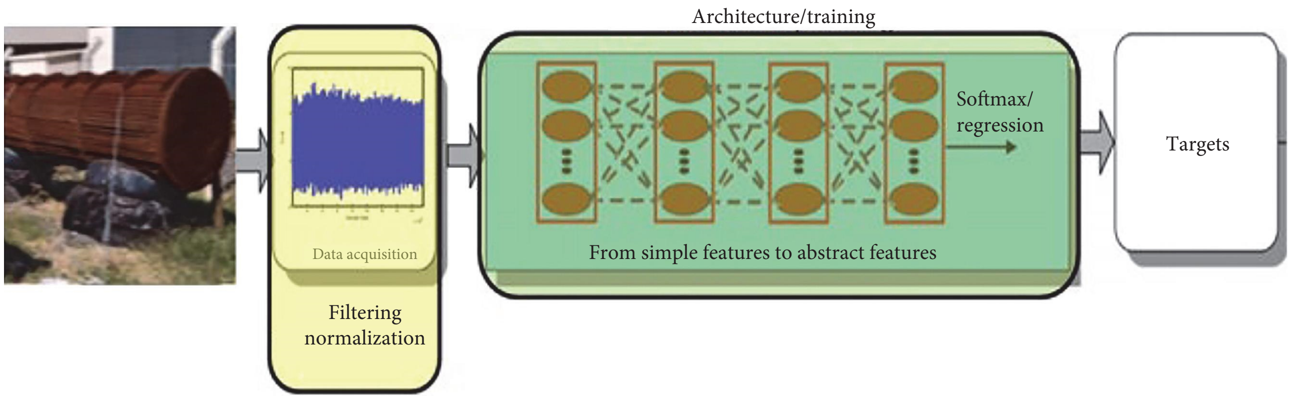

Figure 2: Architecture of the supervised learning.

where, for example, the corrosion rate of the wall of a certain steel tube, i, obtained for inspection of a campaign, thus the input predictors for the network will be operating time and the respective corrosion rate inspected via NDT and the remaining thickness is the label that the network aims to predict the results. In the CNN model, the convolution operation in a convolutional layer is performed through multiplications between kernel functions, $w \in R^{D\times 1}$, of dimension, D, where the concatenation vector, $x_{i:i+D-1}$, is given as:

$$x_{i:i+D-1} = x_i \oplus x_{i+1} \oplus \ldots \oplus x_{i+D-1}, \tag{1}$$

where $\oplus$ indicates the concatenation operation of the sample data in a vector and $x_{i:i+D-1}$ is a window of size, D. In this case, the convolution operation is established as follows:

$$z_l = \varphi(w^T x_{i:i+D-1} + b), \tag{2}$$

where φ and b represent the nonlinear activation and bias functions, respectively, and z_j designates the learned feature of function, w. By sliding the filtering window from the sample points, the feature map can be defined as follows [29]:

$$z_j = [z_1, \ldots, z_{l-D+1}]. \tag{3}$$

Figure 2 illustrates the sequence for prognosis of heat exchangers based on supervised learning, and Figure 3 defines the architecture of the CNN encoder model adopted in this study. The first two layers are formed by 10 filters (3×8) and (3×16), respectively, and the relation between the spatial neighborhood features in the sample is captured by adopting two convolutional layers with 3×32 filters. Here, the functions *relu* and *batch* normalization are retained herein for the grouping of convolution layers. It results in a total of four convolutional layers for the CNN encoder model.

3. Proposed Methodology

For the purposes of training and testing the network model, the inspection dataset was divided into two subsets, where each of it contains a percentage of 70 and 30 of the total inspection data for training and testing process, respectively. The steps of the procedure based on supervised learning for RUL estimation of heat exchangers are shown in Figure 4 and summarized as follows:

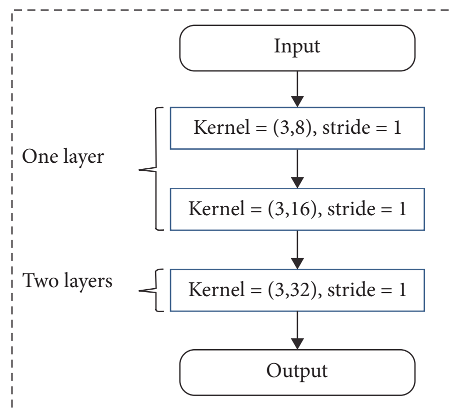

Figure 3: Illustration of the CNN encoder model.

(1) Generating the subsamples using the available data, x, obtained by inspection of n steel tubes for a given campaign. For the purposes of this study, the time of each campaign is divided in m cycles in order to preserve the important information of the corrosion process. For example, for a campaign of 1 year, it can be divided in 12 cycles of 1 month. Then, the corrosion depth for each steel tube as function of time is modeled by using the following Weibull function [10]:

$$x_i(t) = \frac{\beta}{\alpha}\left(\frac{t-t_c}{\alpha}\right)^{\beta-1} \exp\left(\left(\frac{t-t_c}{\alpha}\right)^{\beta}\right), \tag{4}$$

where t_c is the time of the beginning of the corrosion, with $(t-t_c)\geq 0$ and $t = t_c, t_{c+1}, \ldots t_{\text{campaign}}$, and $\alpha = \sqrt{2\sigma(x)}$ and $\beta = E[x]$ are, respectively, the scale and shape parameters,

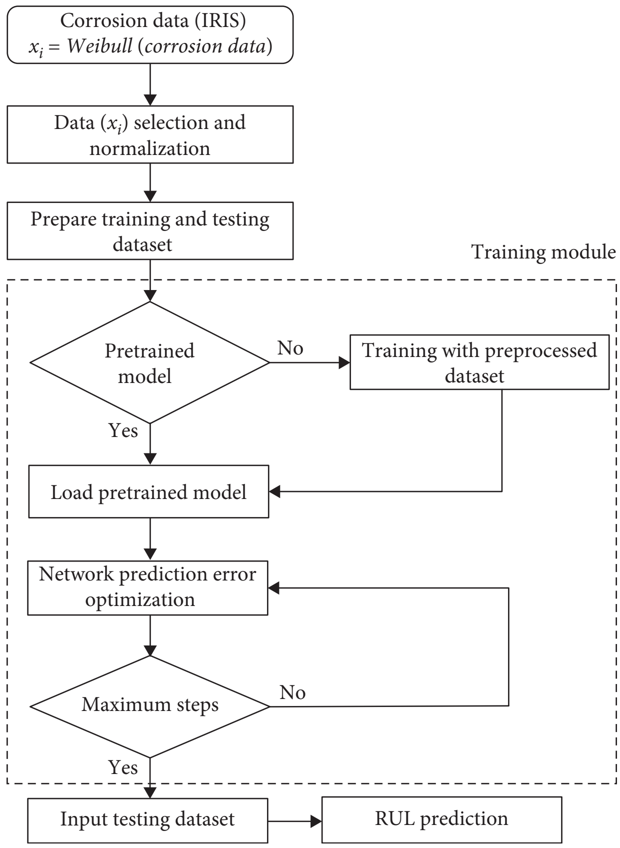

FIGURE 4: Steps of the procedure for heat exchanger prognostics based on supervised learning.

with σ and $E[x]$ being the standard deviation and mathematical expectation, respectively.

(2) Selection and normalization of inspection data features: The important information usually found in technical inspection reports of heat exchangers suffering from corrosion is: nominal diameter and thickness in *mm*; total number of tubes in the system, n; the number of tested tubes, m; inspection date; and location of the defects (thickness' loss in *mm*). Based on inherent distinct features and properties between each set of tubes of a heat exchanger, it is performed herein a preselection process of the data variability. It is based on the mathematical expectation and its normalization values, given, respectively, by the relations $E[(x-\mu)^2]$ and $(x-\mu)/\sigma$, where μ is the mean of the information given by Equation (4). Based on this strategy, it is possible to choose, among the available information, the indicators whose change over the time is used to characterize the corrosion process.

(3) Constructing the dataset for training and testing the metamodel: In this phase, the remodeling process of the normalized corrosion data is performed to obtain a new dataset for training and testing of the 1D-CNN model. As an example, for a 10 sequence of data, as shown in Figure 5, it is generated a total of seven new sequences of data of length four.

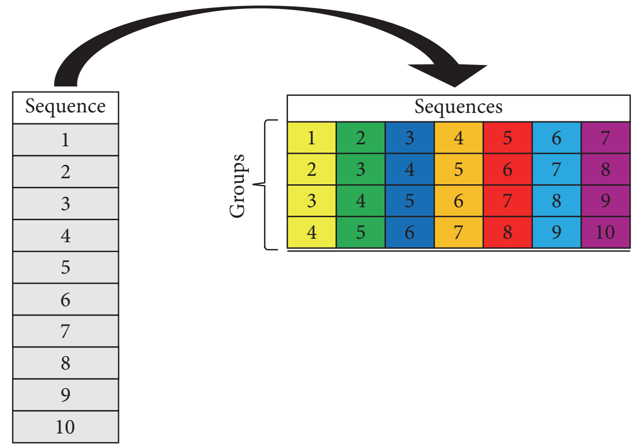

FIGURE 5: Illustration of the remodeling process.

(4) Training of the 1D-CNN model: At this time, it is performed the network training to produce the set of information to approximate the future remaining wall thicknesses of the steel tubes.

(5) Testing of the 1D-CNN model.

(6) RUL prediction: It is done for a certain level of reliability, based on the root mean square error (RMSE) [30]:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{m} (x_i - x_{est})^2}{m}}, \tag{5}$$

where x_{est} is the wall thicknesses estimated by using the 1D-CNN model, and x_i is the value of remaining wall thickness subsampled using EVA-bootstrap.

Hence, the RUL of a given steel tube suffering from generalized corrosion is estimated as:

$$\mathrm{RUL} = t_{\mathrm{est}} - t_{\mathrm{oper}}, \tag{6}$$

where t_{est} is the estimated time for which the tube reaches the minimal wall thickness required for a safe operating condition, and t_{oper} is the operating time for the corrosion state.

At this time, it is important to emphasized that, among the available supervised ANN approaches (similarity, degradation, and survival) focused on RUL predictions, it is retained herein the so-called degradation models, as shown in Figure 6. Since, it requires the periodic information on the equipment operation, which is obtained here by NDT inspection such as the IRIS testing.

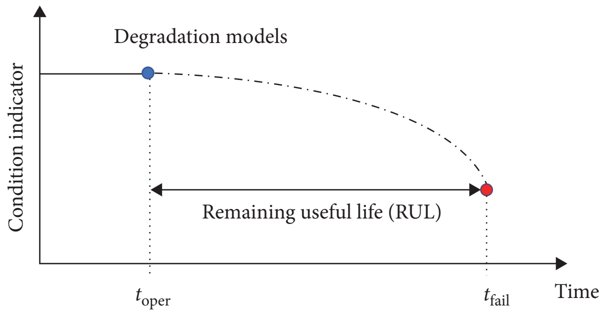

Figure 6: Illustration of the adopted ANN model.

Figure 7: Illustration of the IRIS testing on the heat exchanger system addressed in this study.

Table 1: Technical data of the heat exchanger.

Nominal thickness (mm)	Tube bundle	Inspection tubes	Tested tubes
2.108	775	177	53

Note. Heat exchanger FP-210501-E-10B. Courtesy of REGAP.

4. Results and Discussions

This section presents the main features and potentialities the proposed methodology regarding the prediction of the degradation process occurred on the steel tubes of a real-world heat exchanger system used in a Brazilian oil and gas refinery and their RUL. Again, the dataset is formed by the remaining wall thicknesses of a number of AISI 1018 steel tubes suffering from generalized corrosion. In practice, these minimal thicknesses values have been obtained inspection using the IRIS method [31], which enables to compute the percentage of loss of material of each tube forming the heat exchanger.

Figure 7 illustrates the inspection process of the heat exchanger system addressed herein using the IRIS testing method, whose technical characteristics are given in Table 1.

4.1. Weibull Function and Statistical Tests. From the technical maintenance reports and the information regarding the beginning of the system operation (see Table 1) with the available inspection data at each campaign (in 2006, 2010, and 2016), it is computed the mean of it for each campaign, as shown in Figure 8. Next, Equation (2) is used to interpolate these available data to characterize the evolution of the remaining wall thickness of each tube due to the corrosion process to perform, in the sequence, a bootstrap method to generate the training and testing dataset needed to construct the CNN-1D model.

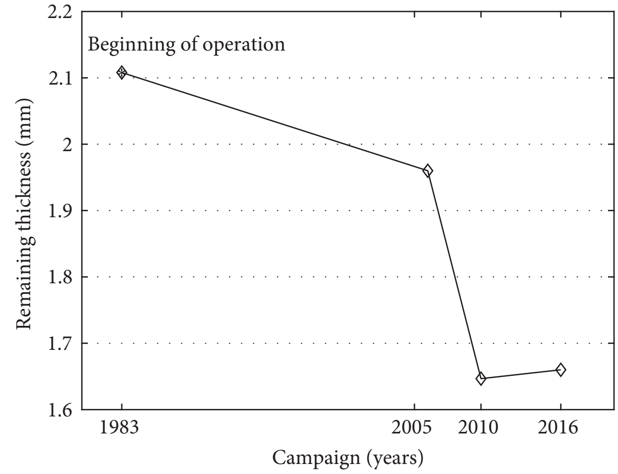

Figure 8: Mean of the remaining wall thicknesses of the steel tubes for three different campaigns.

Figure 9(a) enables to compare the histogram of the available inspection data with the data generated by using Equation (2) for the following values of shape and scale parameters 1.83 and 11.2, respectively. It has been obtained by performing the so-called maximum likelihood approach. By comparing the empirical and theoretical curves of probabilities, as shown in Figure 9(b), it is evident the accuracy of the distribution adopted in this study to characterize the evolution of the remaining wall thicknesses of the steel tubes forming the heat exchanger due to the generalized corrosion process.

The quality of the fitted inspection data to the theoretical data generated by the Weibull function can be verified by using the Anderson–Darling (AD) and Kolmogorov–Smirnov (KS) statistical tests for a significance of 5%. For the purposes of comparison, Table 2 shows the statistical results obtained by using the various distribution functions, where the t-Student is frequently used in oil and gas industry for RUL predictions. It can be perceived a greater adherence of the inspection data to the theoretical data generated by using the Weibull function when compared with the results generated by other distributions. Thus, it explains its adoption in many works [1, 9, 21, 22] appearing in the open literature to characterize the evolution of the remaining wall thicknesses of heat exchanger tubes suffering from generalized corrosion.

4.2. Bootstrap Method. As shown in Table 1, the considered heat exchanger is composed of 775 tubes, of which only 177 have any inspection history throughout their operational period. Consequently, a set of 70% of the inspected tubes was used for training and the remaining 30% was used for testing the 1D-CNN model. Thus, based on the adjust shape and scale parameters of the Weibull function, a subsample of 388 randomized corrosion data per tube is generated in bootstrap, resulting in a total of 20,564 corrosion data points to be used in testing phase of the 1D-CNN approach. Figure 10 illustrates the shape and scale parameters of the dataset tested using the 1D-CNN.

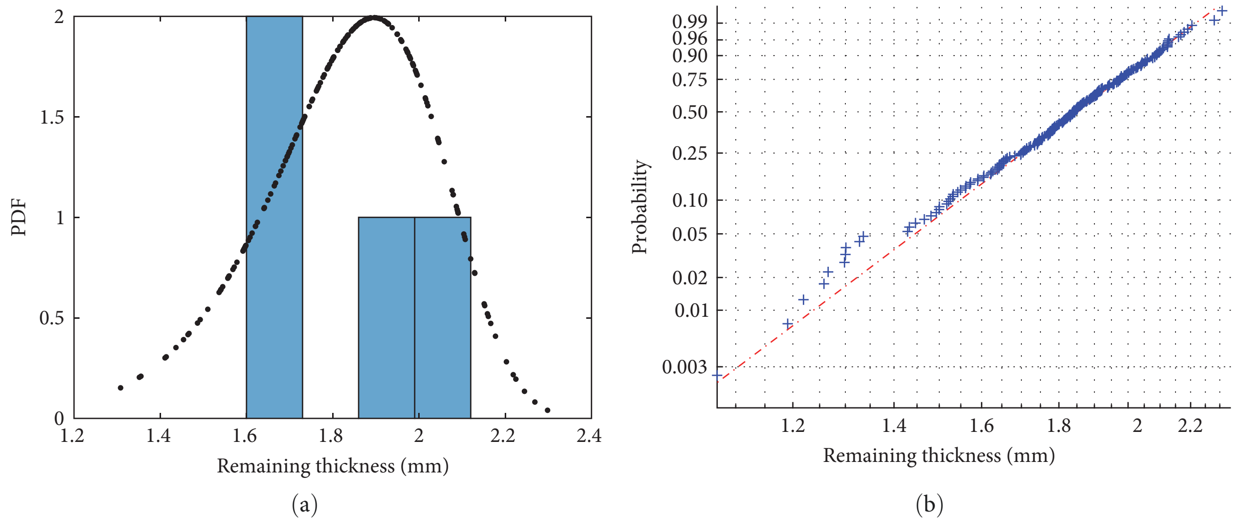

Figure 9: (a) Comparison between the histogram of the available inspection data and the theoretical data generated by the Weibull function; (b) graph of probability for the fitted data.

Table 2: Statistical results for various distribution functions.

Function	KS	AD
Weibull	0.3086	0.1059
Gamma	0.0814	0.0906
EV	0.0862	0.0881
t-Student	0.0814	0.0426
GEV	0.0385	0.0213
GP	0.0702	0.0010

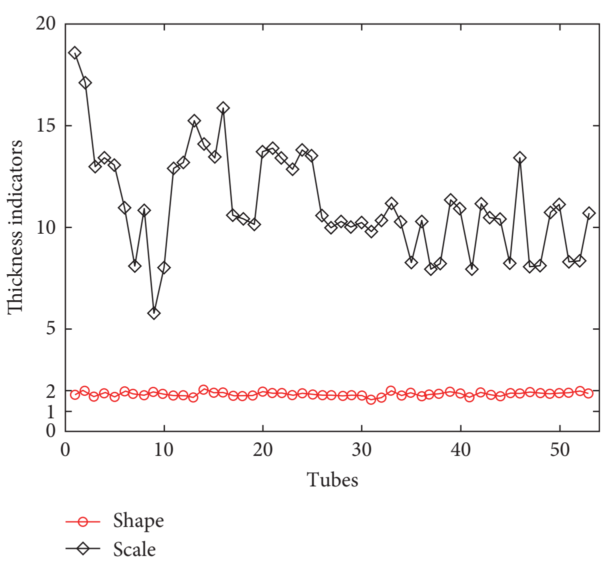

Figure 10: Shape and scale parameters of the tubes.

Figure 11(a) shows the theoretical corrosion data of the tubes generated by the bootstrap, and Figure 11(b) shows the PDFs of the corrosion over the analyzed period.

Before applying the CNN model to estimate the RUL of the steel tubes, it is performed herein a nonparametric statistical analysis in order to verify the quality of the theoretical corrosion data generated by using the bootstrap method. Within this aim, Figure 12(a) shows the histograms of the empirical thicknesses and the subsampling obtained by using the Weibull function for the remaining wall thicknesses. To verify the model using the plotting tools, as shown in Figures 12(b) and 12(c), it has been adopted the AD test, resulting in a *p-value* of approximately 0.0596. Thus, it can be concluded that the measured sample comes from a Weibull function for a significance level of 5%.

4.3. RUL Estimation. Figure 13 shows the histogram of the RMSE distribution, as defined by Equation (5), regarding the corrosion data given by the IRIS inspection method and the data estimated by using the 1D-CNN model over the analyzed period. It can be seen that the RMSE error is comprised in the range of 0.04–0.05 mm, as shown in Figure 13(b). Also, Figure 13(c) shows the scatter for the network's performance, enabling to compare the predicted and true values of thicknesses for the system under investigation.

Figure 14 compares the remaining wall thicknesses predicted by the CNN model with the corresponding obtained by the IRIS tool for the best and worst tubes in terms of corrosion process, which have been obtained from the minimum and maximum RMSE values, respectively.

The tubes having an expected corrosion greater than the average value for a confidence level of 5% are shown in Figure 15. In this case, based on Equation (6), it is possible to establish a confidence interval for the mean and variance of the population, which are given as follows:

$$\left[\mu_{\mathrm{RMSE}} - z_{1-\alpha/2}\frac{s_{\mathrm{RMSE}}}{\sqrt{n}};\ \mu_{\mathrm{RMSE}} + z_{1-\alpha/2}\frac{s_{\mathrm{RMSE}}}{\sqrt{n}}\right], \tag{7}$$

$$\left[\frac{s^2_{\mathrm{RMSE}}(gl-1)}{\chi_{\sup}}; \frac{s^2_{\mathrm{RMSE}}(gl-1)}{\chi_{\inf}}\right], \tag{8}$$

where n indicates the size of the RMSE sample, $gl = n-1$ is its degrees of freedom, μ_{RMSE} and s_{RMSE} are the mean and

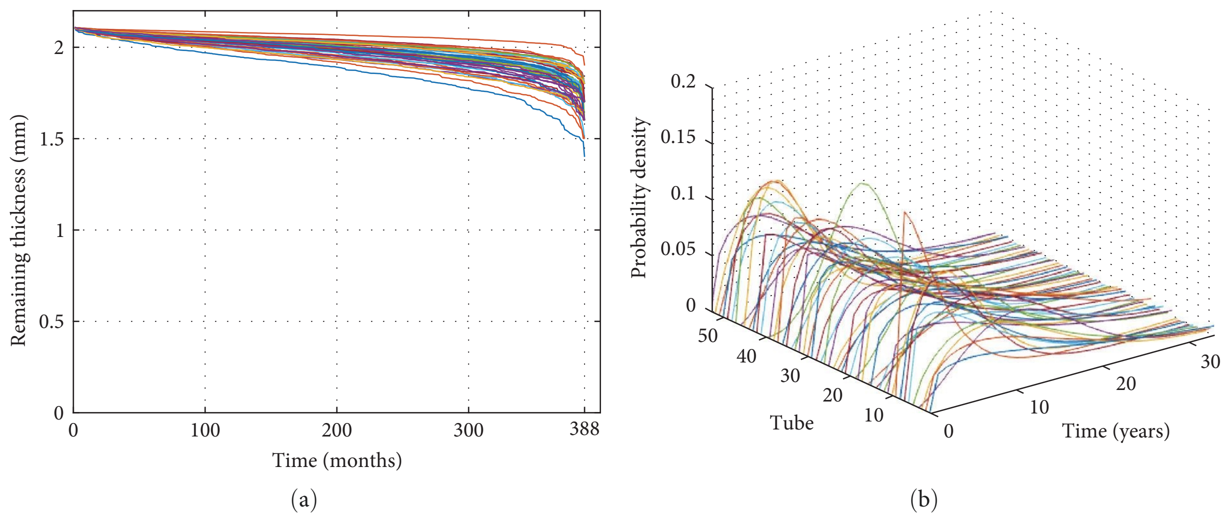

FIGURE 11: (a) Theoretical corrosion data generated by bootstrap; (b) PDFs of the theoretical data.

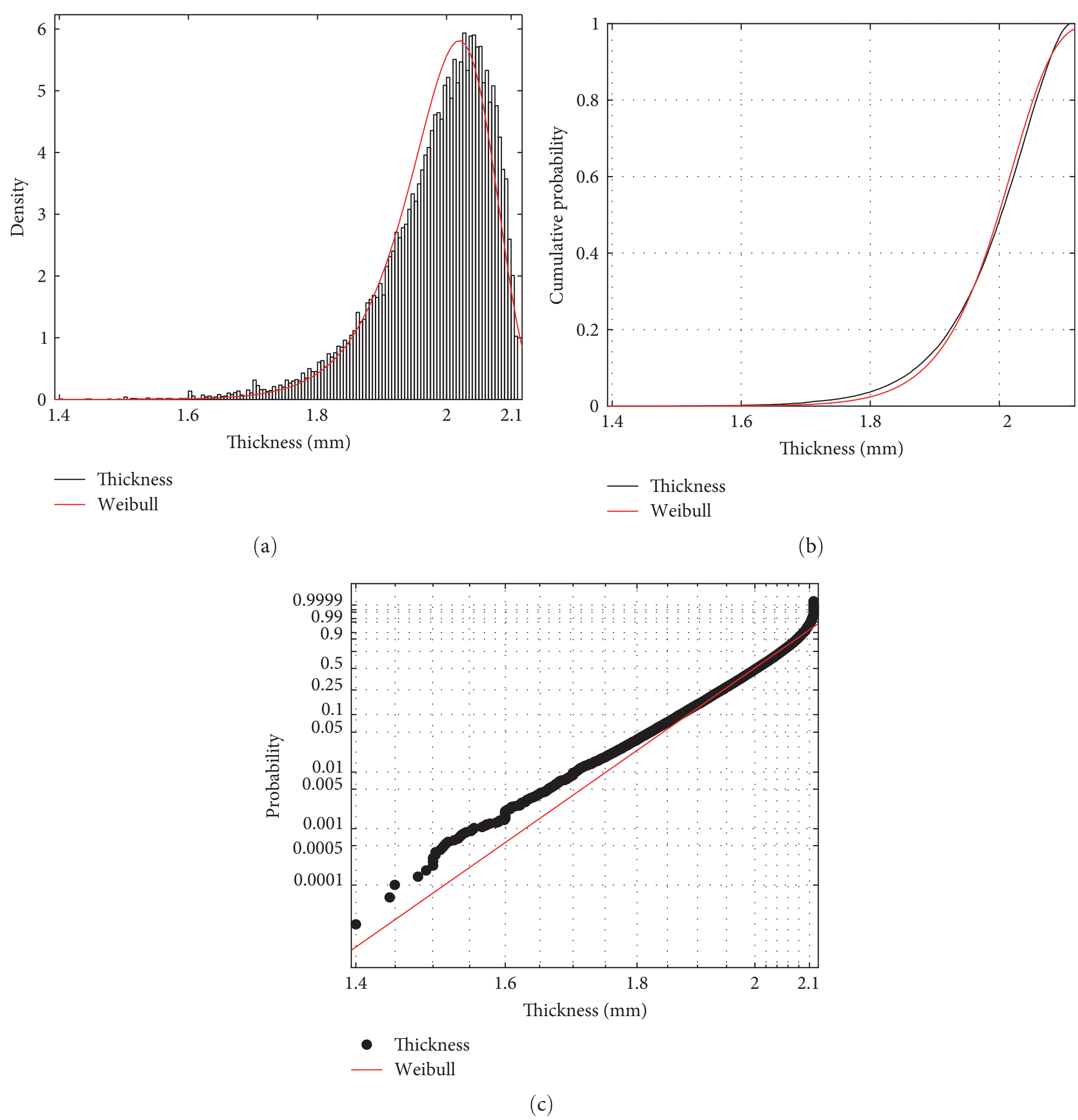

FIGURE 12: (a) Histograms of the remaining wall thicknesses and Weibull function; (b) CDFs of the empirical and theoretical data; (c) probabilities of empirical and theoretical data.

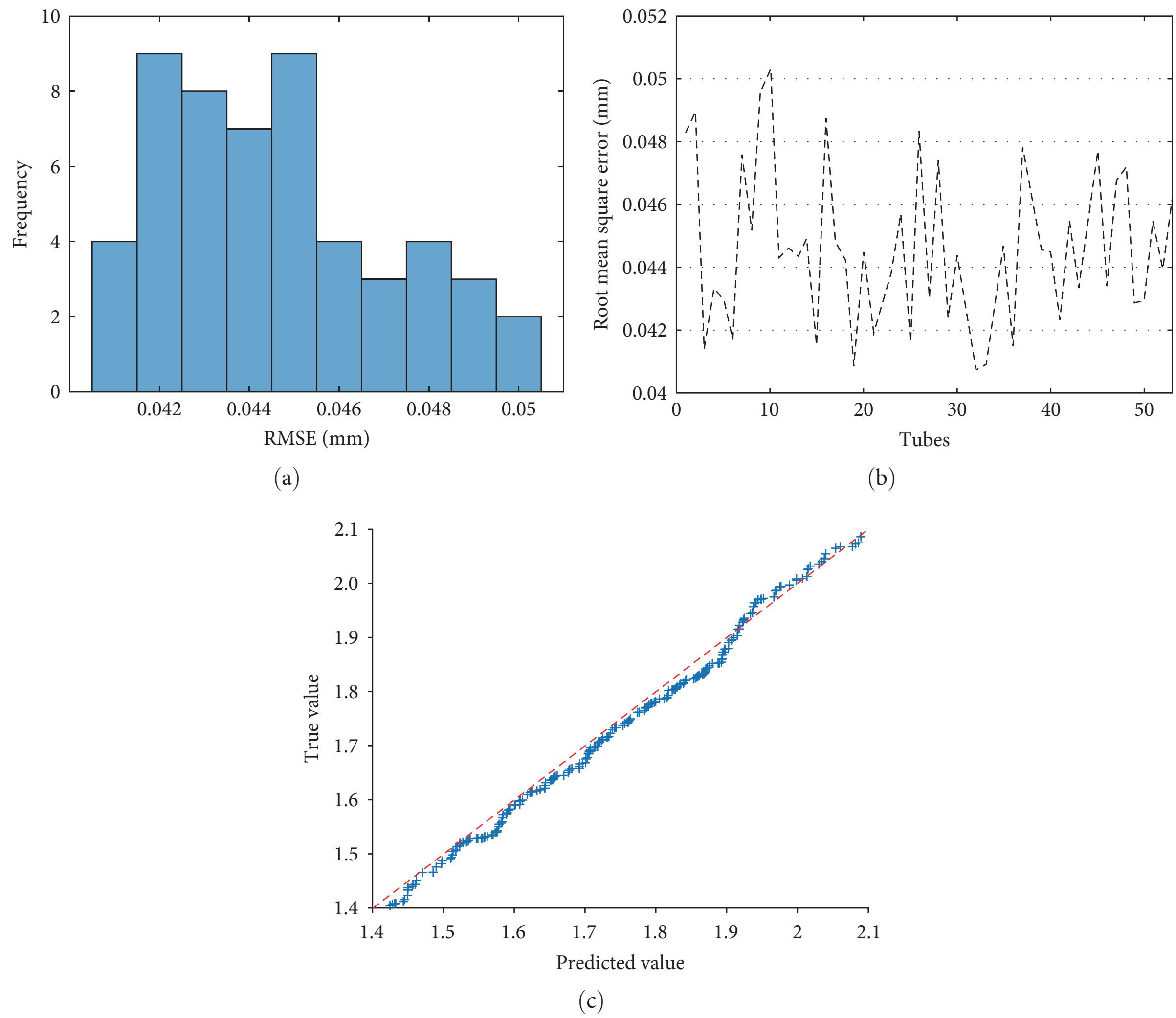

Figure 13: (a) Histogram of the RMSE; (b) RMSE per tube; (c) scatter plot.

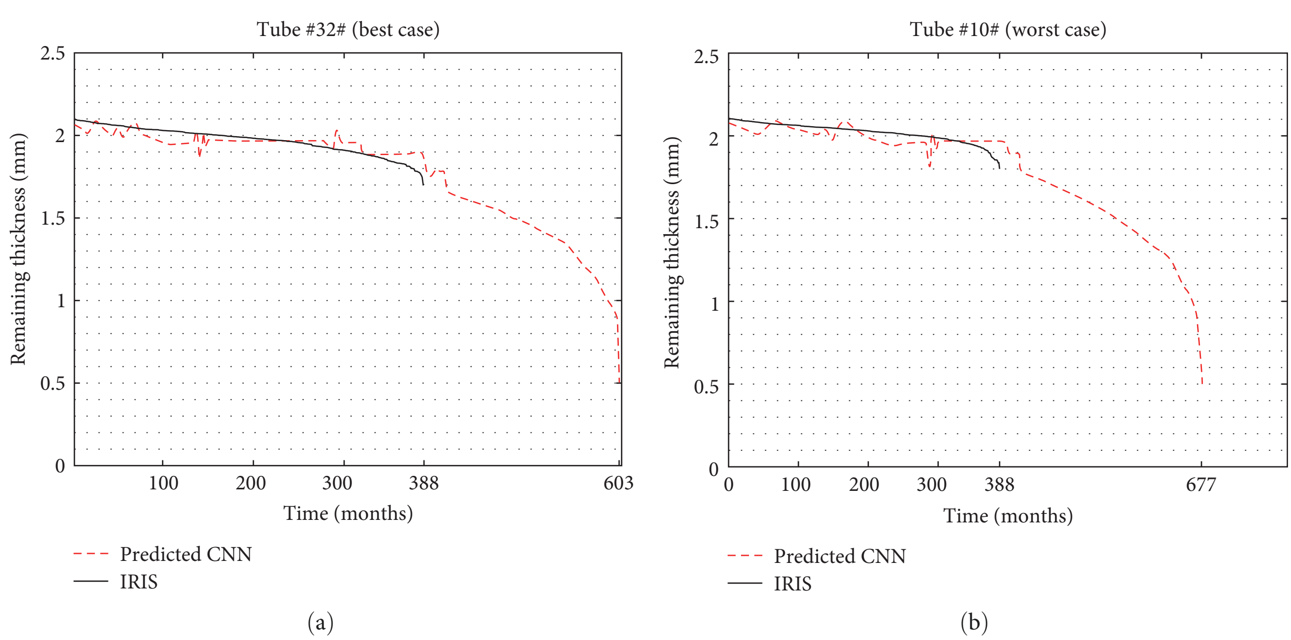

Figure 14: Comparison between the remaining thicknesses given by the CNN-1D and IRIS (a) Smallest approximation error; (b) Largest approximation error.

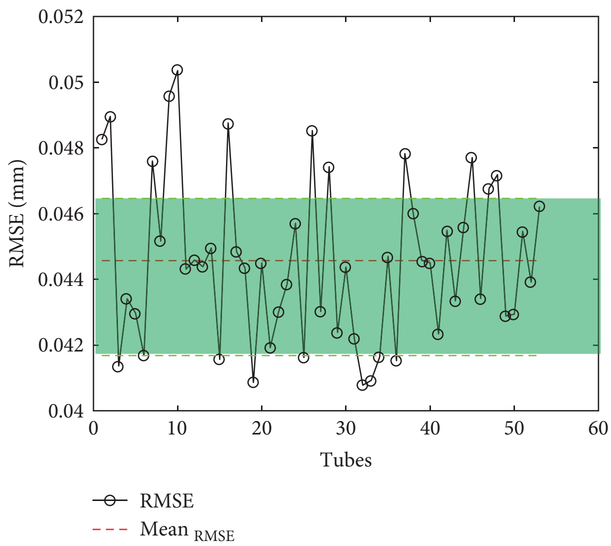

FIGURE 15: RMSE per tube over the operating cycle with a confidence interval for the mean and standard deviation of the population.

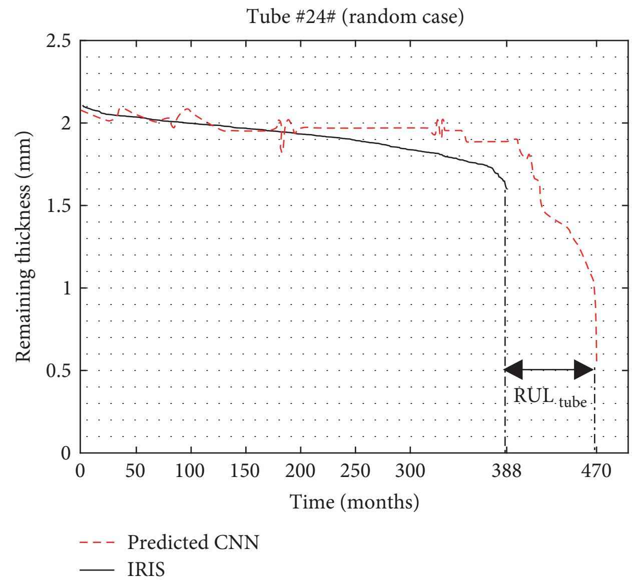

FIGURE 16: Illustration of the RUL computation for a given steel tube during the campaign.

standard deviation of the RMSE sample, $z_{1-\alpha/2} = 1.96$, and $\chi_{\inf}$ and $\chi_{\sup}$ are, respectively, the lower and upper χ^2 values for the confidence level of 5%.

Figure 15 represents the analyzed steel tubes with a RMSE error higher than a significance of 5%, where the steel tubes having a greater probability of failure over the operating cycle considered herein can be clearly identified.

Now, to estimate the RUL of the tubes and, consequently, the heat exchanger, based on Equation (6), it is considered the period of time of a campaign, t_{oper}, and the remaining time, t_{est}, estimated by the 1D-CNN model. Within this aim, as appearing in Petrobras Norm N-26090 [32] and according to the technical maintenance reports available by the petroleum refineries, it suggests a range of 0.5–12.5 mm for measuring the wall thicknesses using the IRIS testing. Thus, for safe operation, 0.5 mm is the minimum value of the wall thickness used in traditional methods to estimate the RUL. As an illustration, for a given heat exchanger tube, Figure 16 shows the RUL that is computed herein.

Figure 17(a) shows the estimated RUL in months of operation of each tested steel tube. It can be perceived a remaining useful life of at least 7.5 years compared with the last inspection that has been performed in 2016. Figure 17(b) shows the remaining thicknesses of each tube in 2016. Table 3 summarizes some important results for the management engineers for the purposes of integrity analysis of the system.

By examining the results, as shown in Table 4, in terms of the number of tubes and their respective percentages of RUL, it is expected that none of the analyzed steel tubes will reach the minimum wall thickness in a period less than 7.5 years. However, in a period until 13 years, it is observed that 34% of the tubes in the bundle will need corrective maintenance to continue operating safely. On the other hand, it is expected that the system can operate approximately 16.8 years without the need of a maintenance. Clearly, it should be mentioned that a corrective maintenance can increase the useful life of the equipment.

4.4. Traditional Method versus Proposed Methodology. In the quest for the traditional method used in industry which is based on the small sample theory [32] in conjunction with the *t*-Student distribution, the minimum wall thickness and its thickness as a function of time due to the corrosion phenomenon are established, respectively, as follows:

$$x_{\min} = \overline{x} - t_{\alpha,gl-1}\left(\frac{s}{\sqrt{n}}\right), \tag{9}$$

$$x(t) = x_{\mathrm{nom}} - \left(\frac{x_{\min} - x_s}{t_{oper}}\right)t, \tag{10}$$

where $\overline{x}$ and s are the sample mean and standard deviation, respectively, n is the number of samples, and $t_{\alpha,\,gl-1}$ is given by using the *t*-Student's table for a significance level, α. $x_{\mathrm{nom}} = 2.108$ mm is the nominal value of the thickness obtained from technical maintenance reports, $x_s = 0.5$ mm is the value of the thicknesses adopted in industry for safe operation, and t_{oper} is the operation time. In this case, the RUL is computed by the relation, $RUL = t - t_{\mathrm{oper}}$.

For example, for the data acquired in 2010, where 18 steel tubes of the bundle were inspected, having $\overline{x} = 1.6$ mm and $s = 0.32$ mm for an operation time of $t_{\mathrm{oper}} = 26.36$years, the industry was found a RUL of 21.5 years, assuming a significance level of $\alpha = 1\%$ with $t_{\alpha,\,gl-1} = 2.898$.

However, by applying the proposed method on the 2006 and 2010 inspection data only, it has been found a RUL of approximately 5.9 years for the tube of the bundle subjected to an extreme corrosion process, as shown in Figure 18.

At this time, it is important to discuss the RUL of 21.5 years estimated by the industry in 2010 for this heat exchanger. According to the information available by the maintenance reports, in 2015, some steel tubes of this system were completely replaced by new steel tubes due to their extreme corrosion state.

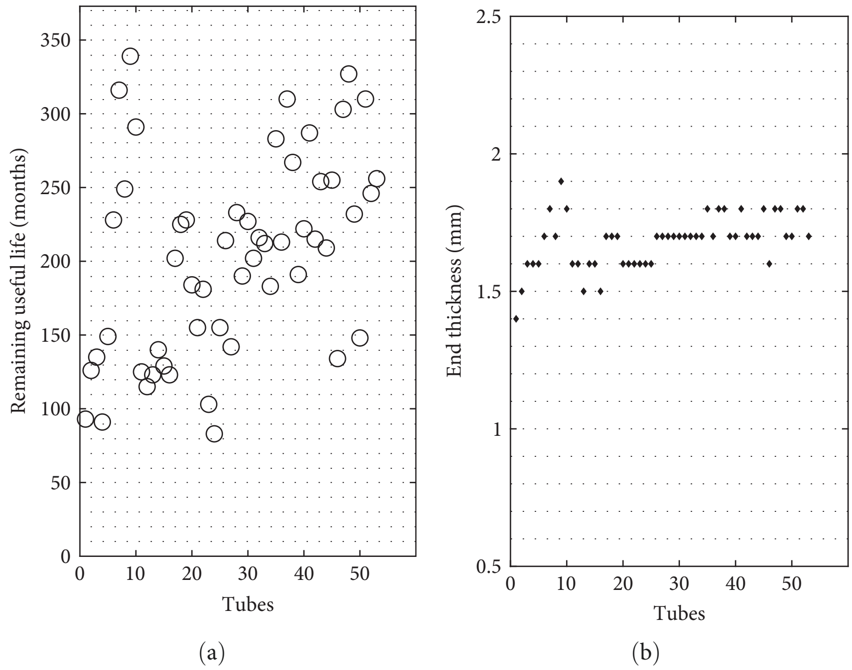

Figure 17: (a) Estimation of the RUL; (b) remaining thickness of each tube tested.

Table 3: Some results given by the CNN model.

Sample	Mean population	Mean sample	Real wall loss	Estimated wall loss
21	1.68 mm	1.68 mm	0.71 mm	0.67 mm

Table 4: Estimated values of the RUL.

%	<20	20–40	40–60	60–80	>80
RUL	0	18	19	13	3

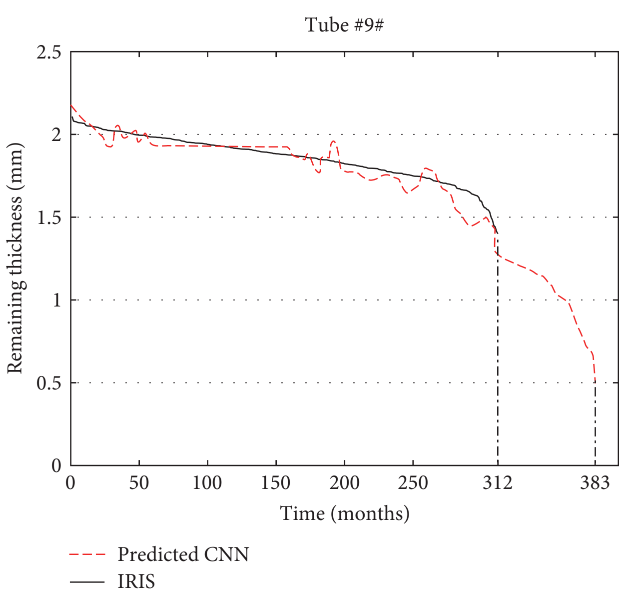

Figure 18: RUL estimation by the proposed method using the 2006 and 2010 inspection data.

Thus, the traditional method is not capable of estimating the RUL of the system with accuracy, since, after 5 years of service, it was necessary to perform a replacement of some tubes of the bundle due to their corrosion state. But, the proposed methodology has estimated a RUL of approximately 5.9 years, demonstrating the accuracy of it compared with the traditional approach used in industry.

5. Concluding Remarks

This work has proposed an interesting method based on the use of AI to increase the accuracy of RUL prediction of heat exchangers used in oil and gas refineries suffering from generalized corrosion. The method uses the Weibull function and bootstrap method to characterize the corrosion process and a 1D-CNN model to predict the RUL. From the inspection data composed by the remaining wall thicknesses of the heat exchanger tubes, it was constructed a randomized nonlinear temporal series' model to extract the meaningful information and the data for the training and testing of the 1D-CNN model. It is important to address the following points:

(1) The use of traditional approaches based on small sample theory is not capable of estimating the RUL of the heat exchanger systems with accuracy, since it has predicted a RUL of 21. 5 years of operation for the system addressed herein, but after 5 years of service, it was necessary to perform a replacement of some tubes of the bundle due to their corrosion process.

(2) The results showed the ability of the proposed pretraining model to characterize the evolution of the remaining wall thicknesses of the tubes suffering from generalized corrosion. However, advances can

be performed in order to refine the 1D-CNN model proposed in this study to make it more accurate and effective. Advances in the quality of measurement data were obtained by NDT testing.

(3) The proposed methodology is a promise tool to help engineers and users for structural integrity analyses of various assets suffering from corrosion. Furthermore, it enables to estimate the minimum sample size required in the inspection phases for statistical inference.

Clearly, in this study, the proposed strategy has been applied in a real-world heat exchanger system used in a Brazilian refinery. However, the authors understand that it is not limited to it and can be extended with advantage to other industrial assets subjected to corrosion.

Data Availability

The corrosion data used in the present study were available by PETROBRAS-BR in accordance with the CENPES Researcher Engineer Weslley Dias da Silva. The corrosion data used to support the findings of this study are currently under embargo during the research.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

The authors are grateful to PETROBRAS for the financial support of this research in cooperation with Federal University of Uberlândia. Also, the authors are grateful to CNPq and FAPEMIG for the continued support to their research activities through the research grants 306138/2019-0 and PPM-0058 (A.M.G. de Lima), respectively, as well as the State University of Goiás/Institutional Platform for Research and Innovation in Bioinputs.

References

[1] I. P. Lemos, A. M. G. de Lima, M. A. V. Duarte, and W. C. D. Silva, "A methodology to estimate the remaining residual life of components of processes subjected to corrosion using the extreme value theory combined with the first-order reliability method," *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, vol. 43, Article ID 499, 2021.

[2] H.-Y. Tan, *Statistical methods for the analysis of corrosion data for integrity assessments*, (Doctoral dissertation), Brunel University London, 2017.

[3] T. Shibata, "Corrosion probability and statistical evaluation of corrosion data," *Uhlig's Corrosion Handbook*, pp. 367–392, 2000.

[4] N. Kasai, S. Mori, K. Tamura, K. Sekine, T. Tsuchida, and Y. Serizawa, "Predicting maximum depth of corrosion using extreme value analysis and Bayesian inference," *International Journal of Pressure Vessels and Piping*, vol. 146, pp. 129–134, 2016.

[5] C. Melo, M. Dann, R. J. Hugo, and A. Janeta, "Extreme value modeling of localized internal corrosion in unpiggable pipelines," *International Journal of Pressure Vessels and Piping*, vol. 182, Article ID 104055, 2020.

[6] M. Yamamoto and T. Shibata, "Program for calculating the extreme value statistics on the spreadsheets software (EVAN-II)," *Corrosion Science and Technology*, vol. 1, no. 3, pp. 228–233, 2002.

[7] A. J. McNeil, "Extreme value theory for risk managers," *Departement Mathematik ETH Zentrum*, vol. 12, no. 5, pp. 217–237, 1999.

[8] L. T. Popoola, A. S. Grema, G. K. Latinwo, B. Gutti, and A. S. Balogun, "Corrosion problems during oil and gas production and its mitigation," *International Journal of Industrial Chemistry*, vol. 4, Article ID 35, 2013.

[9] M. H. Mohd, D. K. Kim, D. W. Kim, and J. K. Paik, "A time-variant corrosion wastage model for subsea gas pipelines," *Ships and Offshore Structures*, vol. 9, no. 2, pp. 161–176, 2014.

[10] Y. Bai, Y. Kim, H.-B. Yan, X.-F. Song, and H. Jiang, "Reassessment of the jacket structure due to uniform corrosion damage," *Ships and Offshore Structures*, vol. 11, no. 1, pp. 105–112, 2016.

[11] C. I. Ossai, "Pipeline corrosion prediction and reliability analysis: a systematic approach with Monte Carlo simulation and degradation models," *International Journal of Scientific & Technology Research*, vol. 2, no. 3, pp. 58–69, 2013.

[12] Z. Zangenehmadar and O. Moselhi, "Assessment of remaining useful life of pipelines using different artificial neural networks models," *Journal of Performance of Constructed Facilities*, vol. 30, no. 5, Article ID 04016032, 2016.

[13] K. Le Son, M. Fouladirad, A. Barros, E. Levrat, and B. Iung, "Remaining useful life estimation based on stochastic deterioration models: a comparative study," *Reliability Engineering & System Safety*, vol. 112, pp. 165–175, 2013.

[14] K. Le Son, M. Fouladirad, and A. Barros, "Remaining useful lifetime estimation and noisy gamma deterioration process," *Reliability Engineering & System Safety*, vol. 149, pp. 76–87, 2016.

[15] C. Gong and W. Zhou, "First-order reliability method-based system reliability analyses of corroding pipelines considering multiple defects and failure modes," *Structure and Infrastructure Engineering*, vol. 13, no. 11, pp. 1451–1461, 2017.

[16] J. K. Paik and D. K. Kim, "Advanced method for the development of an empirical model to predict time-dependent corrosion wastage," *Corrosion Science*, vol. 63, pp. 51–58, 2012.

[17] R. Zhao, R. Yan, Z. Chen, K. Mao, P. Wang, and R. X. Gao, "Deep learning and its applications to machine health monitoring," *Mechanical Systems and Signal Processing*, vol. 115, pp. 213–237, 2019.

[18] N. Yamamoto, A. Kumano, and M. Matoba, "Effect of corrosion and its protection on hull strength (2nd report)," *Journal of the Society of Naval Architects of Japan*, vol. 1994, no. 176, pp. 281–289, 1994.

[19] Mathworks, "Predictive Maintenance Toolbox: RUL Estimation Models. Disponible in," Accessed in 15 Mai 2021

[20] A. Saxena, K. Goebel, D. Simon, and N. Eklund, "Damage propagation modeling for aircraft engine run-to-failure simulation," in *2008 International Conference on Prognostics and Health Management*, pp. 1–9, IEEE, Denver, CO, USA, 2008, October.

[21] A. Coppe, M. J. Pais, R. T. Haftka, and N. H. Kim, "Using a simple crack growth model in predicting remaining useful life," *Journal of Aircraft*, vol. 49, no. 6, pp. 1965–1973, 2012.

[22] F. Di Maio, S. S. Ng, K. L. Tsui, and E. Zio, "Naive Bayesian classifier for on-line remaining useful life prediction of degrading bearings," MMR2011, pp. 1–14, June 2011.

[23] J.-P. Kreiss and S. N. Lahiri, "Bootstrap methods for time series," *Handbook of Statistics*, vol. 30, pp. 3–26, 2012.

[24] K. Jarrett, K. Kavukcuoglu, M. Ranzato, and Y. LeCun, "What is the best multi-stage architecture for object recognition?" in *2009 IEEE 12th International Conference on Computer Vision*, pp. 2146–2153, IEEE, Kyoto, Japan, 2009 September.

[25] A. Voulodimos, N. Doulamis, A. Doulamis, and E. Protopapadakis, "Deep learning for computer vision: a brief review," *Computational Intelligence and Neuroscience*, vol. 2018, Article ID 7068349, 13 pages, 2018.

[26] T. Ince, S. Kiranyaz, L. Eren, M. Askar, and M. Gabbouj, "Real-time motor fault detection by 1-D convolutional neural networks," *IEEE Transactions on Industrial Electronics*, vol. 63, no. 11, pp. 7067–7075, 2016.

[27] O. Abdeljaber, O. Avci, S. Kiranyaz, M. Gabbouj, and D. J. Inman, "Real-time vibration-based structural damage detection using one-dimensional convolutional neural networks," *Journal of Sound and Vibration*, vol. 388, pp. 154–170, 2017.

[28] G. Hou, S. Xu, N. Zhou, L. Yang, and Q. Fu, "Remaining useful life estimation using deep convolutional generative adversarial networks based on an autoencoder scheme," *Computational Intelligence and Neuroscience*, vol. 2020, Article ID 9601389, 14 pages, 2020.

[29] F. Elasha, S. Shanbr, X. Li, and D. Mba, "Prognosis of a wind turbine gearbox bearing using supervised machine learning," *Sensors*, vol. 19, no. 14, Article ID 3092, 2019.

[30] K. V. Shatalov and A. D. Cherepanova, "Verification of the hypothesis of compliance of the errors of the results of analyses of oil products to the normal distribution law for a random variable," *Measurement Techniques*, vol. 62, pp. 905–914, 2020.

[31] M. F. Saffiudeen, A. Syed, and F. T. Mohammed, "Failure analysis of heat exchanger using Internal Rotary Inspection System (IRIS)," *Journal of Failure Analysis and Prevention*, vol. 21, pp. 494–498, 2021.

[32] "Petrobras N-2690 Norm," August 2023, https://bcend.com.br/tag/petrobras-n-2690/.