A review on oil and gas pipelines corrosion growth rate modelling incorporating artificial intelligence approach

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Abstract. One of the necessities of an effective oil and gas pipeline safety Management Plan (SMP) is the establishment of safe and efficient risk assessment strategy for pipelines where the significant danger is corrosion. Corrosion growth is related to several factors involving pipe material, pipe condition, and defect geometrical imperfection. Thus, the assurance of a proper corrosion assessment requires the prediction and evaluation of corrosion growth rates. The prediction of corrosion growth rate precisely, would minimize the cost of pipelines maintenance through the determination of the deteriorated pipeline segments. In line inspection (ILI) has been used to detect the pipelines corrosion, also the corrosion can be detected by other inspection tools such as Magnetic flux leakage (MFL) and Ultrasonic tool (UT). However, there are numerous models have been utilized to anticipate the corrosion growth rate such as deterministic and probabilistic models. Recently, there are conducted researches on the application of artificial intelligence in predicting corrosion growth rate for oil and gas pipelines such as artificial neural network (ANN) and fuzzy logic (FL). This paper aims to provide a comprehensive comparison between the conventional methods, i.e. deterministic and probabilistic and artificial intelligence methods, i.e. Artificial neural network (ANN) and fuzzy logic (FL) in the prediction of corrosion growth rate of oil and gas pipelines. This review would be helpful to pipelines operators to understand the effectiveness of artificial intelligence approach compared to conventional methods in corrosion growth rate modelling.

1. Introduction

Pipelines are very important in the oil and gas industry for safe delivery of oil/gas products whether on offshore or onshore environment. They are normally made of carbon steel. Therefore, corrosion is taken into consideration as primary danger to the pipeline’s serviceability. Corrosion of pipelines is depending on the time factor where pipelines consequently get corroded as they get older [1]. Therefore, it is necessary to assess and predict the corrosion growth rates to avoid pipeline failures or leakages. In addition, prediction of corrosion growth rate can be used to carry out risk assessment to make decisions by pipeline operators[2]. ILI have become one of the favored tools to assess the status of the pipes. There are many tools of ILI including Ultrasonic Tools (UT) and Magnetic Flux Leakage (MFL), which have different precisions. In Line Inspection datasets are usually utilized to forecast the corrosion growth rate [3].

Corrosion growth calculation can be utilized in future inspection planning, planned excavation, costing and pipeline operators’ decisions(maintenance/replacement), etc. Corrosion growth give an approach to anticipate what the corrosion status of the pipelines in different ages. Although, corrosion growth rate determination will also identify the corroded areas of the pipes. [4]. These defects can be identified by using appropriate corrosion rate models. Thus, defining the correct corrosion growth rate models are significant to decide if the corrosion rate is low so, the maintenance or replacement should take place or the corrosion rates are high so, the assessing the pipelines condition will be
unnecessary[5]. Regarding to this, when the datasets are collected from Non-Destruction test or ILI, corrosion rates ought to be identified as the method for pipelines safety planning and management (for instance, to decide the suitable reinspection time for pipelines). For these reasons, distinctive corrosion growth rates models have been developed for long period. of time[6]. All these models describe the local corrosion of pipelines (for example intergranular corrosion rate). The local corrosion happen on the inner and outer pipes surface specific deepness[7]. In current practice, the pipeline operators and researches are using either conventional or artificial Intelligence corrosion growth rate models. The following sections will explain more about conventional and artificial corrosion growth rate modelling.

2. Types of corrosion
The electro-chemical interaction between the metal and its surrounding environment would bring various types of corrosion. The most widely recognized one is pitting. Others likewise incorporate galvanic intergranular, crevice, velocity effected corrosion, stress cracking corrosion, general corrosion and selective leaching corrosion as shown in Figure 1. Also Figure 2 provides schematic illustration of a typical corrosion defect geometry.

![Figure 1. Various types of corrosion established on certain metal surface](image1.png)

![Figure 2. Schematic illustration of a typical corrosion defect geometry](image2.png)

3. Corrosion growth rate models
Some of the conventional corrosion growth rate models which have been used recently are deterministic and Probabilistic models. On the other hand, the most common artificial intelligence corrosion growth rate models are artificial neural network models and fuzzy based models.

3.1. Conventional corrosion growth rate modelling
The term of Conventional or traditional corrosion modelling can be used for both deterministic and probabilistic corrosion growth models. Deterministic and probabilistic models consist of various modelling approaches[10]. The difference between deterministic and probabilistic method are discussed as follows:
3.1.1 Probabilistic models. Probabilistic modelling can be used when uncertainties of pipelines occur. In this case, probability will be considered a variable and probable situation must be taken in consideration by means of statistical approaches. There is an essential hypothesis for entirely probabilistic models, where all uncertainties are considered when modelling the corrosion growth rates of oil/gas pipelines [11]. Brief explanation of some well-known probabilistic models are introduced bellow:

3.1.1.1 Time dependent generalized extreme value distribution. The Time Dependant Generalized Extreme Value Distribution (TDGEVD) modelling depends on time variation of corrosion with respect to time distribution for widely spread texture soils. The factors in this characteristic differ with respect to time for the determination of the genuine pitting corrosion rates distribution in buried pipes. The equation (1) can describe the corrosion pit growth rate distribution for buried pipelines [12]:

\[ G(\vartheta) = \exp\left\{ - \left[ 1 + z\left(\frac{\vartheta - \mu}{\sigma}\right)^{-\frac{1}{\gamma}}\right]\right\} \]

\( \vartheta \): Corrosion rates variance  
\( \mu \): distribute position  
\( \sigma \): distribute gage  
\( \gamma \): Shaping parameter

3.1.1.2 Time independent generalized extreme value distribution. Time Independent Generalized Extreme Value Distribution is same to Time dependent Generalized Extreme Value Distribution excepting that the hypothesis of factors of the GEV corrosion rate distribution is constant and equivalent to the factors at the time of initial inspection. Whereas, TDGEVD can anticipate deformity depth distribution at upcoming moment of time, then it can be compared with the investigated distribution and the outcome from other probabilistic models [13].

3.1.1.3 Monte-Carlo simulation. One of the recognized probabilistic factorized investigation approaches is the Monte-Carlo modelling. The “traditional” Monte-Carlo modelling is utilized as an uncertainty evaluation of a deterministic calculation as it yields a distribution identifying the possibility of alternative probable values about the nominal factor [14]. The most important gain of the Monte-Carlo modelling is that it does not require complex evaluation. A first-rate limitation of this model is that the mathematical version of the investigated system needs to solve ratings of time to get an appropriate population for statistical evaluation. This may require a longer calculating time [15].

3.1.1.4 Markov modelling. The Markov modelling can also be classified as a probabilistic modelling. Corrosion growth distribution by the Markov modelling utilizes a non-stop-time or non-homogenous linear growth approach. The Markov method can model Markov model can predict pitting corrosion in buried pipelines. Also, assess the wall thickness of pipelines from soil properties and coating type. The application of this probabilistic method needs to identify the soil parameter and the initial wall thickness of the buried pipelines. The exponent \( \vartheta \) as in equation (2) is stand for the soil type. The value of \( \vartheta \) differs for one of a different soil textural classes and relies on specific characteristics such as soil capacity, bulk density of the soil, soil water content and pipeline coating type [14].

\[ p_n(t) = \sum_{m=1}^{n} p_m(t_0) \left( \begin{array}{c} n-1 \\ n-m \end{array} \right) \frac{\vartheta^m}{m!} \left( t - t_{ini} \right)^{\vartheta^m} \left( 1 - \left( \frac{t_0 - t_{ini}}{t - t_{ini}} \right)^{\vartheta^m} \right) \]

The figure (3) shows the probabilistic density function (PDF) for different corrosion growth rate models. Among the investigated models it was shown that the Markov model was more accurate in corrosion rate evaluation [14].
Figure 3. Probabilistic density function for corrosion growth with rate (0.1 mm per year) using some corrosion growth rate models [16].

Changing the found deformity depth to Markov state components leads to identifying of depth distribution with respect to probability \( p_m(t_0) \) for the depth in a state equivalent to or lesser than \( m \) at time \( t_0 \). Equation (2) and (3) identify the possibility of a deformity being in state \( n(n \geq m) \) at time \( t = t_{init} + \delta t \) [17].

\[
\frac{n - 1}{n - m} = \frac{(n-1)!}{(n-m)(m-1)!}
\]

In equation (2), \( t_{init} \) and \( \delta t \) represent the non-linear time development of the corrosion depth in pipelines consistent with equation (2) whereas, \( t_0 \) links to the time which \( p_m(t_0) \) represent the time of preliminary inspection. The age and size of the corrosion along with pipeline characteristics and soil properties allow the Markov model to predict corrosion growth effectively more than other probabilistic methods. [18].

3.1.1.5 The Brownian motion with drift modelling. The Brownian Motion with Drift (BMWD) model considered as a probabilistic method that assumes corrosion as random process. Also, it can be utilized to model creeping and wearing phenomenon. The advantage of this approach is that corrosion flocculently decreases and increases (like trading share value), thus it is not advisable for slow deterioration procedure. But it can be ideal for estimation in term of corrosion growth rate with random deformity shape. example of Brownian Motion With Drift model in figure 4.0 [19].

Figure 4. Illustration of realizations of the Brownian motion[19].
3.1.1.6 Gamma process modelling. Like gaussian distribution, the gamma method is continuing probability distribution determined by using only two factors, $\theta$ for scaling and $k$ for shaping. The Probability Density Function (PDF) of gamma distribution can be calculated using equation (4) and (5):

$$f(x|k, \theta) = \frac{x^{k-1}e^{-x/\theta}}{\theta^k(k)}$$  \hspace{1cm} (4)

$$k = \int_0^\infty t^{k-1}e^{-t}dt$$  \hspace{1cm} (5)

Figure 5 shows the Gamma distribution for distinct $k$ and $\theta$ number. It can be seen that the shape of distributed gamma entirely changed unlike gaussian distributions where the mean easily changes the variation (standard deviation) then compresses the curvature [20]. The gamma process is more precise with big datasets. Therefore, it can be used to model corrosion growth rate with available In Line Inspection data [21].

![Figure 5. Gamma distributing plot for different $\theta$ and $k$ numbers [20]](image)

3.1.2 Deterministic modelling. Corrosion growth rate modelling by deterministic models can be used in some cases when the corrosion rates are linear, non-linear and single value corrosion. These deterministic approaches depend on the availability of in line inspection data and the operator’s experience. The three above mentioned approaches can be explained as follows:

3.1.2.1 Linear corrosion growth rate modelling. The linear corrosion growth rate models are used to forecast the depth of corrosion over a period. This is achieved through the assumption of the linear behaviour of growth rates as it can be seen in equation (6)[22]:

$$h(t) = h_0 + h't$$  \hspace{1cm} (6)

$h(t)$: the depth of corrosion deformity over a period
$h'$: corrosion rate
$t$: the time when the corrosion appears or in other word the deformity depth at the time $t_{ini}$

Corrosion Growth Rate regularly can be determined by two datasets from two ILI as it can be seen in equation (7)[23]:
\[ h' = \frac{dT_2 - dT_1}{T_2 - T_1} \]  

(7)

\( h' \): corrosion growth rate  
\( dT_2 \): the metal loss in the last In Line Inspection.  
\( dT_1 \): the metal loss in the first In Line Inspection.  
\( T_2 \): time interval of the last In Line Inspection.  
\( T_1 \): time interval of the first In Line Inspection.

Regarding the above, there are two known methods to calculate the corrosion growth rate. Firstly, is signal matching and secondly defect matching. The signal matching compares two In Line Inspection signals. The outcome of this method can calculate the corrosion growth rate with high accuracy comparing to defect matching method[24]. Thus, for oil and gas pipelines, pipelines characteristics and segmentations might be compared for any pipeline segment contains high corrosion growth rate.

### 3.1.2 Nonlinear corrosion growth modelling

The distribution of corrosion growth rate that utilizes reliability prediction of buried pipelines could also be explained in nonlinear modelling based on the pipeline operator’s familiarity with pipes materials and soil. The limitation of this model is the availability of inspection datasets and knowing the soil characteristics of buried oil and gas pipelines. The equation (8) express the deterministic non-linear corrosion growth rate [16]:

\[ (ht) = \alpha(t - t_{int})^\theta \]  

(8)

\( \vartheta, \alpha \): pipeline soil dependence factors.  
\( t_{int} \): Initial time of the corrosion.

#### 3.1.2.3 Single Value Corrosion Growth Rate Modelling

The Single Value Corrosion Growth Rate Modelling is extensively utilized to determine the corrosion growth rate rather than other deterministic methods. The Single Value Corrosion Growth Rate Modelling use constant corrosion rate such as the rate that included in NACE standard (0.4 millimetre per year) as standard corrosion rate for tracking the corrosion depth development over the analysis [25]. The limitation of this method is the independency on the depth and the age defects of corrosion growth [13].

### 3.2 Artificial intelligence corrosion growth rate modelling

Recently, there are many researchers used Artificial intelligence to determine the corrosion growth rate of oil and gas pipelines. Some of this artificial intelligence methods are:

#### 3.2.1 Artificial neural network (ANN)

In oil and gas pipelines industry the availability of enough datasets to be used in the corrosion growth rate modelling (assessment and prediction) is the biggest challenge. Therefore, the artificial neural network (ANN) method is very efficient in assessment and prediction of corrosion growth rate, based on limited datasets. The artificial neural network imitates the power of the human mind in prediction, through the training and testing process. ANN is a very accurate prediction method in oil and gas pipelines, since it is capable to learn from the available inspection data. Rachman [26]specified that artificial neural network is a simulation method that is good to apply when interconnect features among parameters are mysterious. Layouni [27]stated that artificial neural network is convenient in problems representation when the resolutions are unclear and the connection between the input and output variables are not clearly recognized. As can be seen in figure (6) The artificial neural network is consisting of many artificial perceptron’s that are stochastically organized in various layers (inputs, hidden layers and outputs).
M. S. El-Abbasy [29] developed an ANN model for the prediction of the oil and gas pipelines condition by using In Line Inspection dataset from major oil and gas company in Qatar. They concluded that corrosion growth rate increases when the metal loss increasing and decreases when the cathodic protection of the pipeline carefully maintained. M. M. Din [30] used ANN in oil and gas pipelines to develop a corrosion growth rate model that depends mainly on time. The developed ANN model has predicted the corrosion length and depth of the pipe deformation that might be utilized to get the corrosion growth rate score. C. Wang [31] used support vector machine (SVM) for the prediction of corrosion growth in offshore oil and gas pipelines. The model predicted the corrosion growth rate of offshore oil and gas pipelines with a very small error. M. Smith [32] discovered that the utilization of the dataset analysing method to enhance the corrosion growth rate prediction comes after repeated In line Inspection method to detect the corrosion rate in oil and gas pipelines. Precise corrosion growth rate from Signal Matching (a new precise corrosion growth rate method based on computer visions) was used in the training of supervised machine learning model. The developed model improved the corrosion growth rate from Box Matching Analysis (accuracy is not high, but the method is widely used to predict corrosion growth rate).

3.2.2 Fuzzy Logic. Fuzzy logic was introduced for the first time in 1965 by Zadeh [33]. Fuzzy logic is the degree of membership that uses multiple values. Fuzzy logic deals with approximation and inaccurate language terms like (high, medium, small, critical) better than fixed numbers such as neural networks [34]. Fuzzy logic is very efficient in modelling the incomplete facts apprehensions. Moreover, the inputs and outputs functions can be utilized to demonstrate the linguistic parameters. In general, fuzzy logic is consisting of fuzzy rules and fuzzy reasoning, fuzzy inference systems and fuzzy sets. [35]. Figure (7) shows one of the fuzzy logic methods which is fuzzy inference system.

F. Mosleh [33] developed fuzzy based condition model for the assessment and the prediction of an offshore gas pipeline condition. The model gives a satisfactory outcome in offshore gas pipelines condition prediction. A. Senouci [36] also used fuzzy logic model in the prediction of pipeline failure. The fuzzy based model was able to successfully anticipate the pipeline failure. V. Biezma [37] predicted the external corrosion rate by combining six measured soil variables with less inspection datasets. This approach can be utilized by pipelines operators in the optimization of the serviceability of the pipes.
4. Comparison between conventional and artificial intelligence methods in the prediction of the corrosion growth rate

Based on various developed models in corrosion growth rate modelling, the artificial intelligence outperformed the conventional methods (deterministic and probabilistic models) in terms of accuracy and simplicity. The following table 1 demonstrates the advantages and disadvantages of the two corrosion growth rate modelling methods (Artificial intelligence modelling and conventional modelling).

Table 1. Advantages and disadvantages of conventional and artificial intelligence corrosion growth rate models.

| Corrosion growth rate modelling type | Method                           | Advantages                                                                 | Disadvantages                                                                                                                 |
|-------------------------------------|----------------------------------|----------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------|
| Conventional corrosion growth rate modelling | Deterministic modelling          | • This method focuses on single scenario with known corrosion type.         | • Unknow corrosion information’s prevent the pipelines operators to use deterministic method.  
• The inspection dataset most be at least two inspection data to conduct deterministic corrosion growth modelling. |
| Probabilistic modelling             |                                   | • It considers all the uncertainties in modelling corrosion growth rate.    | • More complicated and contains a lot of misunderstanding.  
• Can be used to model corrosion growth rate with an incomplete data or limited inspection datasets. |
| Artificial intelligence corrosion growth rate modelling | Artificial neural network         | • Artificial neural network algorithms easily can be learned.              | • ANN models users must have knowledge in computer programming which is not easy for ANN users from different study areas. |
modelling methods in case simulating large inspection datasets.

- The result accuracy is very high and can be represented in scores.
- ANN can accomplish complicated tasks based on given training data.

| Fuzzy logic                  | Overtraining for the datasets by using ANN algorithms may lead to wrong results. |
|------------------------------|----------------------------------------------------------------------------------|
| - Fuzzy logic is an intelligent method which can be used and implemented easily. |                                                                                    |
| - User friendly with understandable linguistic terms and simple equations.   |                                                                                    |
| - Fuzzy logic algorithms can be explained with less rough data.              |                                                                                    |
| - It is hard to identify the proper linguistic terms for the membership value of fuzzy system. |                                                                                    |
| - Fuzzy logic can be utilized to resolve problems if information about solution in the linguistic term if then rule. |                                                                                    |

5. Conclusion
Corrosion growth rate modelling (assessment and prediction) is a very complicated process due to the various influencing factors on the pipeline. The modelling of corrosion growth rate has become a big concern by pipelines operators and researchers, to identify the best methods to detect the corrosion and predict its impact on the pipeline whether short term impact or long term impact. Based on extensive studies and inspections the pipeline operators will decide if the existing oil/gas pipelines need maintenance or replacement. Presently, there are two methods in modelling corrosion growth rates which are conventional or traditional method and artificial intelligence method. Conventional method has been used for long time based on two approaches which is probabilistic and deterministic approaches. In other hand the second corrosion growth rate modelling method is artificial intelligence which consider the most recent technique and more accurate comparing to the traditional method.

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