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ESTIMATION OF THE CORROSION RATE OF BURIED METALLIC MATERIALS BY A NEURO-FUZZY EXPERT SYSTEM

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Abstract

There is no doubt that determination of corrosion rate of metals in aggressive environments is critical to prevent future failures in service, thereby saving economic and social costs. However, it is well known that accurate estimation of corrosion rate is a difficult task because it needs to take into account the effect of many different and dynamic variables, which are involved in the electrochemical processes through relationships that are highly complex and difficult to quantify. This is the case of oil and gas buried pipelines, wherein corrosion is mainly linked with soil properties, leading to premature service failure. As attempt to address this issue, the present work proposes a neuro-fuzzy expert system for estimating the corrosion rate of buried pipes in terms of measurable environmental factors.

Keywords: Pipeline; Corrosion; Soil; Fuzzy logic

Introduction

The economic and social costs of pipeline failures are very significant, putting increasing pressure on operators to make decisions on annual network renewal plans, which involve a balance between necessary investments and expected benefits, in a context of risk management. In addition to the need for a clear strategy to address these multi-objective issues, operators need robust and reliable failure models to assess the state of the network as it ages.

The first step in determining the evolution of corrosion phenomena must be to establish the relationship between some measurable environmental properties and the observed corrosion rate. There are essentially three different procedures that can be used to establish this linkage. Firstly, there is a direct empirical correlation between actual corrosion rate measurements and the environmental conditions of buried steel pipes in representative soils. Next, there is the possibility of laboratory measurements and models for corrosion rate estimation. Finally, it is possible to establish detailed numerical models, based on reasonable assumptions, which make corrosion rate predictions based on the environmental variables considered, without experimental measurements of any kind. Each of these procedures has advantages and disadvantages. However, they all require checking the predicted values against actual data taken from cores exposed to the same conditions as the rest of the pipeline, in the same type of soil.

There are several statistical and mathematical techniques that have been developed to model pipeline deterioration, including deterministic, probabilistic/statistical, artificial intelligence-based and combined models. Those based partly or entirely on artificial intelligence have the advantages of being insensitive to noise in the data, are able to automatically detect underlying non-linear phenomena and are able to handle both numerical data and non-quantifiable information. In recent years, fuzzy logic-based methods have been successfully applied to a variety of engineering problems, from the evaluation of concrete structures to water quality modelling and, of course, the prediction of the evolution of corrosive processes in oil and gas pipelines [1,2].

For many practical problems, the available information is vague. Sometimes, measured data and even expert knowledge is too imprecise, albeit very valuable, and difficult to express numerically. Fuzzy logic provides a way to handle qualitative knowledge in numerical reasoning [3]. Neuro-fuzzy modelling harnesses two very powerful artificial intelligence techniques: fuzzy logic provides the tools to handle ill-defined, multivalued and noisy data; neural networks allow learning from input data to provide increasingly accurate forecasts on output variables [4].

In this line, the present work aims to develop a software code based on an Expert System for the evaluation of corrosion in oil and gas buried pipelines, which can be an effective tool for the prediction of the risk of appearance and evolution of anomalies due to loss of external wall thickness by corrosion, with the capacity of learning by inference from data of real cases obtained during operation of the pipeline network.

Background

The assessment of the corrosion rate in buried pipelines is essential for prediction of remaining service life of the structure and is also the most difficult task in well-integrity surveillance programs, amongst others, because it depends on a multitude of parameters. The very nature of the steel with which the pipe is manufactured is fundamental, but so is the type of soil in which the pipeline is buried and the corrosion protection system that has been implemented in the section of pipeline considered. Each of these three factors, which eventually determine the corrosion rate of the wall pipe (material, soil type and corrosion protection), depend in turn on many other variables. With regard to the material, the type of steel used (composition and properties) and the possible alterations due to the thermal cycles experienced by the material close to welds can give rise to corrosion problems located in regions with anodic behaviour. As regards the soil in which the pipe is buried, there are many variables that determine its corrosivity, including concentration of sulphates and chlorides, resistivity, pH, IR-free potential and moisture content. Finally, as regards the corrosion protection measures adopted, the type and condition of the piping coating is decisive, as is the design and efficiency of the cathodic protection system applied to pipeline installation.

Therefore, as can be seen, numerous factors play a role in determining the corrosion rate of steel in a pipeline. However, not all of these variables have the same importance and the interactions between all of them are complex, so that they can never be considered independently of each other.

If corrosion rate is needed to be known in order to make decisions to ensure the structural integrity of the pipeline, to estimate the remaining life of the pipeline or, simply, to know the economic implications that the gradual deterioration of the installation, it is essential to be able to make reliable temporal projections on the evolution of this type of anomalies throughout life in service.

These projections have traditionally been based on information collected from other operators (if accessible for public consultation), indications given in the implementing legislation (which is usually very conservative) and in the company's own data based on its experience of operating the pipeline (which relates to the information collected in the ILI inspection campaigns, in the study of in-service incidents and any *ad hoc* studies that may have been carried out). However, even if all this information were available, well-ordered and documented, projections of the future evolution of the anomalies are in the hands of the company's corrosion technicians. This work is highly conditioned by the experience of these technicians, their ability to analyse an enormous amount of information and the need to translate all this into a very concrete value for the corrosion rate of advance in each localized anomaly. In any case, this work can easily be lost as the technicians responsible for carrying out the work reach their retirement age, because their valuable experience is difficult to pass on to the new evaluators.

For all these reasons, as in other fields of engineering, there is a need to implement expert systems that allow the full power of computer applications prepared for this purpose to be used, preserving the experience and highly specialised knowledge of the company's personnel, while at the same time handling and integrating in a rational way the enormous amount of information generated by the continuous operation over time of the pipeline network.

Structure of the Expert System

The way to address these types of issues, where the final result requested (corrosion rate) depends on a multitude of variables, which are difficult to quantify and with a relationship between them that makes the response highly non-linear, requires the use of expert systems based on fuzzy logic. The fuzzy logic is based on the use of variables that are neither totally true nor totally false, that is, whose values are in an intermediate point between two possible extreme values. While classical or binary logic only contemplates two possibilities, and multivalued logic allows several possible values, the greater complexity of fuzzy logic makes it a more precise method, since its way of understanding a disjunctive is closer to reality. Therefore, the fuzzy logic allows working with intermediate values within a scale, so that it is possible to deal with imprecise or ill-defined information. As an example, if binary logic only works with 0 and 1, fuzzy logic admits decimal values between these two terms. In other words, while classical logic assigns membership or non-membership to a set, fuzzy logic assigns a degree of membership to that set.

Regarding unacceptable anomalies, the use of realistic models adjusted to the characteristics of each pipeline will be considered, in order to establish the foreseeable evolution of the anomalies related to corrosion of the external wall of the pipe, from their current state to the moment when they become unacceptable anomalies (defects). For this purpose, a neuro-fuzzy adaptive model is proposed, with learning capability from real data that will be gradually supplied to the system.

An adaptive neuro-fuzzy inference system (ANFIS) is a fuzzy logic-based system whose operating parameters are not fixed in advance, but are adjusted as the system "learns" from real in-service behavioural data that technicians gradually feed into it. The system gradually makes more accurate predictions of corrosion rates under various combinations of variables involved, using input/output training data obtained from field and laboratory measurements. One of the difficulties of fuzzy logic-based models is to have adequate fitting parameters. Neuro-adaptive learning systems work in a similar way to how neural networks learn and self-correct as they are fed with relevant information. All this information, which is available within the company or may be available in the future if the way in which this information is collected from the facility's operation and control systems is properly planned, will be gradually integrated into the adaptive neuro-fuzzy model. In this way, all this valuable information will be appropriately used for decision making since the company's *know-how* will be able to be consolidated within specifically designed application software and will prevent the technical capability that now resides in the hands of certain people who will not be working for the company forever from being forgotten or lost.

The basic structure of a fuzzy logic expert system is shown in Figure 1.

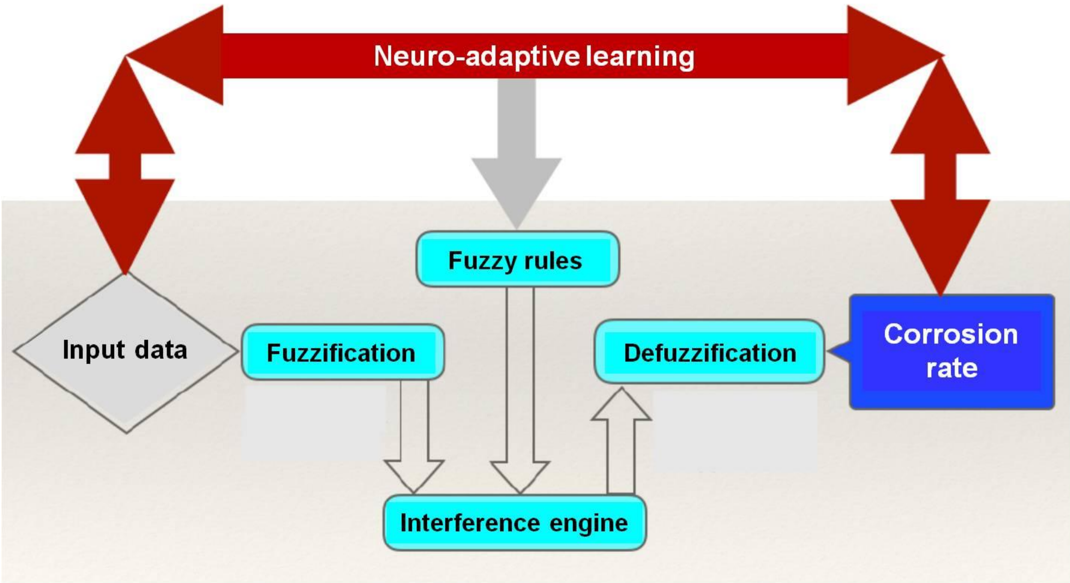

Figure 1. Block diagram of a fuzzy logic expert system.

With regards to the fuzzy method, the algorithm comprises different stages:

a. Situation analysis.

The problem in the case study is investigated with special emphasis on its cause. Usually, the determining factors are linguistic variables, i.e. variables that do not correspond to an exact numerical value (position, size, temperature, etc.). Linguistic variables are input and output variables in the form of simple words or sentences.

b. Knowledge acquisition.

The system uses IF-THEN instructions to carry out the analysis. In this stage, knowledge about the case study is obtained to be subsequently converted into IF-THEN rules within the fuzzy system. To achieve this, previous researches may be used or experts in the sector may need to be involved.

c. Data collection.

Within the enormous variety of data that can comprise a system, it is necessary to select those that are vital for the analysis of the problem. Some data can be in a format that is not compatible with a fuzzy system (e.g. graphs or diagrams), so it is necessary to convert them to a more suitable format.

d. Fuzzification.

The input data is discretized, being converted into fuzzy sets, so that it is necessary to know the function system (or the numerical range of the inputs) and its composition. Thus, the input values must be bounded within the specified system. The fuzzy subset *A* is defined by a membership function and is determined by the following function:

$$A = \sum_{i-1}^{n} \mu_A(x_i)/x_i$$

For the data set *X*, x_i is the element of subset *A and* μ_A is the membership function of x_i element of the system, the input being finite. In this wok, the system is divided into the following ranges: unacceptable (U), barely acceptable (BA), just acceptable (JA), good (G) and very good (VG).

Figure 2 shows a fuzzy gragh, a method by which the degree of membership of a known value can be established.

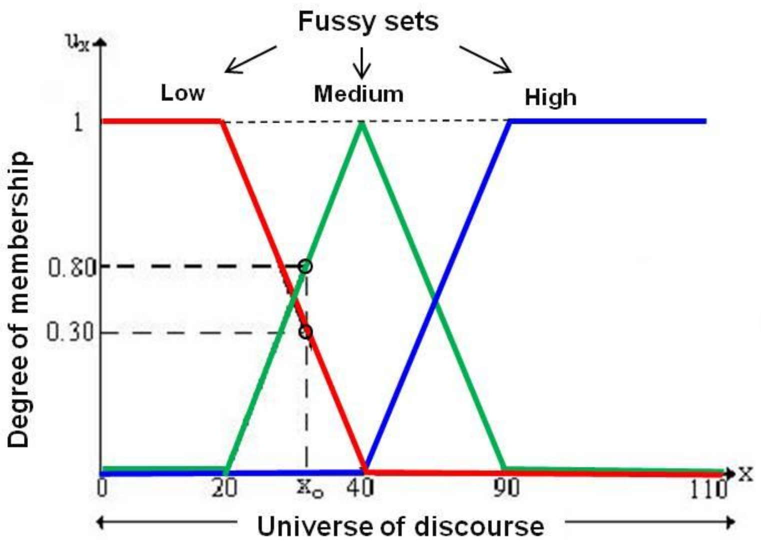

Figure 2. Fuzzy graph.

e. Fuzzy inference engine.

With the fuzzy inference engine, the input for the fuzzy system is converted into the output fuzzy set by means of a discretization procedure using a blocking rule, the general composition, the rule activation, the implication and the aggregation. Depending on the complexity of the system, the number of rules varies. Each fuzzy is composed by an IF-part and a THEN-part, so that ambiguous terms can be used when establishing the rules.

f. Defuzzification.

This is the last stage of the fuzzy method, where the linguistic value (crisp) is obtained by defuzzification. In this step, the center of the area, the maximum probability, the center of mass or other useful defuzzification methods can be used, depending on the conditions given in each case.

Case study of a buried pipeline

As a practical case, the neuro-fuzzy expert system was applied to estimate the corrosion rate of a buried metal pipeline that can suffer deterioration due to corrosive soil environment, assuming the characteristics of the soil in which the pipeline was buried, as shown in Table 1. The proposed neuro-fuzzy expert system entails six soil parameters, which are the input variables: sulphate concentration (ppm), chloride concentration (ppm), pH, IR-free potential (mV), moisture content (%) and resistivity (Ω·m). In addition, the deterioration degree was also introduced as input in the system. From these values, the probability of corrosion associated to each of these variables can be obtained, according to the following classification: extremely likely (EL), very likely (VL), likely (L), not very likely (NL), unlikely (U), very unlikely (VU) and extremely unlikely (EU). Then, the fuzzy graphs are used to obtain the degree of membership for the known values by examining them in pairs. Thus, the sulfate concentration leads either to 0.970 (VG) or 0.029 (G), the chloride concentration implies either 0.143 (JA) or 0.857 (BA), the pH entails 0.4 (G) or 0.6 (VG) and the IR-free potential involves 0.98 (U) or 0.02 (BA). Finally, the moisture content and the resistivity lead to a membership grade of 0.36 (BA) or 0.636 (U) and of 0.675 (BA) or 0.325 (JA), respectively.

Sulfate concentration (ppm)	170	0,97037037	VG	0,02962963	G	0,02962963	NL
		0,02962963	G	0,97037037	VG	0,02962963	NL
Chloride concentration (ppm)	3000	0,14285714	JA	0,14285714	JA	0,14285714	NL
		0,85714286	BA	0,85714286	BA	0,85714286	L
pH	7,3	0,4	G	0,4	G	0,02	NL
		0,6	VG	0,6	VG	0,4	L
IR-free potential (mV)	101	0,98	U	0,02	BA	0,02	L
		0,02	BA	0,98	U	0,6	L
Moisture content (%)	63	0,36363636	BA	0,36363636	BA	0,325	NL
		0,63636364	U	0,63636364	U	0,36363636	NL
Resistivity (Ωm)	2,3	0,675	BA	0,325	JA	0,325	NL
		0,325	JA	0,675	BA	0,63636364	L
Deterioration degree	Medium						

Table 1. Calculation of degrees of membership.

Considering the input variables to be worked with, the fuzzy inference engine will be used to estimate the corrosion rate. The input variables are sulfate concentration (ppm), chloride concentration (ppm), pH, IR-free potential (mV), moisture content (%), resistivity (Ω·m) and degree of deterioration. This last variable will determine the inference engine used, so that depending on the degree of deterioration, the engine used will vary. Table 2 shows the fuzzy inference engine for the first pair of data, considering a medium deterioration degree.

		Medium deterioration degree				
		Sulfate concentration (ppm)				
		U	BA	JA	G	VG
Chloride concentration (ppm)	U	L	L	L	NL	NL
	BA	L	L	NL	NL	NL
	JA	L	NL	NL	NL	U
	G	NL	NL	NL	U	U
	VG	NL	NL	U	U	U

Table 2. Fuzzy inference engine for the first pair of data.

From the fuzzy deduction engine unit, the IF-THEN conditions are generated, with which the implicit corrosion rate will be estimated in each case. In this case they will be the following rules:

- Rule 1: If (IF) the sulfate concentration is VG and the chloride concentration is JA, then (THEN) the degree of membership associated with the corrosion rate is U.
- Rule 2: If (IF) the sulfate concentration is VG and the chloride concentration is BA, then (THEN) the degree of membership associated with the corrosion rate is NL.
- Rule 3: If (IF) the sulfate concentration is G and the chloride concentration is JA then (THEN) the degree of membership associated with the corrosion rate is NL.
- Rule 4: If (IF) the sulfate concentration is G and the chloride concentration is BA, then (THEN) the degree of membership associated with the corrosion rate is NL.
- Rule 5: If (IF) the pH is VG and the IR-free potential is BA, then (THEN) the degree of membership associated with the corrosion rate is NL.
- Rule 6: If (IF) the pH is VG and the IR-free potential is U, then (THEN) the degree of membership associated with the corrosion rate is NL.
- Rule 7: If (IF) the pH is G and the the IR-free potential is BA, then (THEN) the degree of membership associated with the corrosion rate is NL.
- Rule 8: If (IF) the pH is G and the IR-free potential is U, then (THEN) the degree of membership associated with the corrosion rate is NL.
- Rule 9: If (IF) the moisture content is BA and the resistivity is BA, then (THEN) the degree of membership associated with the corrosion rate is L.
- Rule 10: If (IF) the moisture content is BA and the resistivity is JA, then (THEN) the degree of membership associated with the corrosion rate is NL.
- Rule 11: If (IF) the moisture content is U and the resistivity is BA, then (THEN) the degree of membership associated with the corrosion rate is L.
- Rule 12: If (IF) the moisture content is U and the resistivity is JA, then (THEN) the degree of membership associated with the corrosion rate is L.

Once the rules are determined, the IF-parts that have been found can be composed. For each rule, the smallest value of the fuzzy function μ is chosen, as shown in Table 3.

Composition of results	
Rule 1	(0,029^0,14)=0,029
Rule 2	(0,029^0,857)=0,29
Rule 3	(0,97^0,14)=0,14
Rule 4	(0,97^0,857)=0,857

Table 3. IF-THEN rules for the first 4 rules.

Each of these rules implies a probability of increase in the corrosion rate so that, after finding them by calculating their area in the fuzzy graph, the program can proceed to defuzzification by the center of area method, as shown in Table 4. Finally, from the quotient of summations, knowing the progression of the corrosion rate it is possible to find its value. In this case, the estimated corrosion rate was 0,058 mm/year.

	Area (A)	Center of gravity (C)	Weight (w)	A*C*w	A*w
Rule 1	0,7297668	50	1	36,4883402	0,7297668
Rule 2	0,7297668	50	1	36,4883402	0,7297668
Rule 3	3,31632653	50	1	165,816327	3,31632653
Rule 4	12,244898	62,5	1	765,306122	12,244898
Rule 5	0,495	50	1	24,75	0,495
Rule 6	8	62,5	1	500	8
Rule 7	0,495	62,5	1	30,9375	0,495
Rule 8	10,5	62,5	1	656,25	10,5
Rule 9	6,8046875	50	1	340,234375	6,8046875
Rule 10	7,43801653	50	1	371,900826	7,43801653
Rule 11	6,8046875	50	1	340,234375	6,8046875
Rule 12	10,8471074	62,5	1	677,944215	10,8471074
			Σ	3946,35042	68,4052571

$$(\sum_j w_j C_j A_j)/(\sum_j w_j A_j) = 57{,}69$$

Corrosion rate (mm/year)	0,05806819

Table 4. Centroid defuzzification for estimating the corrosion rate.

Conclusions

A methodology based on a neuro-fuzzy expert system has been developed for estimating the corrosion rate of buried metallic materials in terms of measurable environmental factors, which are involved in the electrochemical processes through relationships that are highly complex and difficult to quantify and requires the use of expert systems based on fuzzy logic. As a practical case, the expert system software has been applied to evaluate the corrosion rate of a buried pipe as a function of different characteristics of the soil in which the pipeline is buried, including sulphate and chloride concentrations, pH, IR-free potential, moisture content and resistivity, which have been proven to be of high importance in underground pipe corrosion. The proposed software is expected to be a useful tool for the prediction of the risk of occurrence and evolution of anomalies by loss of thickness of external wall due to corrosion in pipelines, with the ability to learn by inference from actual case data obtained during network operation.

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