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Fuzzy modeling to define corrosivity potential in oil pipelines

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Abstract

In this work, a Fuzzy logic model was developed using the Fuzzy Logic Toolbox™ of the MATLAB® software, for monitoring the corrosivity potential in oil pipelines whose corrosion mechanism is predominantly by microbiological action. With the use of operational parameters, the model presents itself as an alternative to conventional monitoring methods, allowing to infer the corrosion rate in the pipeline, and therefore, the corrosivity potential. The model was applied to an oil pipeline and its results were compared with conventional monitoring methods. The analysis of the results concluded that the model can be used as a monitoring method for pipelines with those predominant corrosion mechanisms, helping to manage the integrity of oil pipelines.

Keywords: Pipeline; Oil; Corrosion; Integrity; Fuzzy Logic.

1. Introduction

Pipelines, in the global context, are the safest means of transport, in operational terms, and the most economical when it comes to hazardous substances, including Oil (Biezma, Agudo & Barron, 2018).

However, a potential damage to the structure of a pipeline may contribute to increase the risk of leaks with great impact on the environment and people. In this way, the structural integrity of the pipeline is of great importance for the oil and gas operating companies, the community close to these pipelines, governments and other interested parties, due to the possibility of environmental, infrastructure and financial losses in case of failure in its integrity (Badida, Balasubramaniam & Jayaprakash, 2019).

The studies carried out on the subject of pipeline integrity have generally addressed analyzes of risks to integrity, involving all threats throughout its life cycle. An example of this can be seen in the research by Kraidi, Shah, Matipa & Borthwick (2020), which addressed risk factors during the design of oil pipelines and gas pipelines. Another work was by Dawuda, Berrouane-Taleb & Khan (2021), who in their research created a probabilistic model to assess the influence of microbiological action on the corrosion rate in pipelines in operation.

By the way, according to the work Khan, Yarveisy & Abbasi (2021), which approached with risk-based integrity management of pipelines, corrosion, after third-party action, is the main cause of damage to the structural integrity of pipelines.

In fact, corrosion is one of the biggest reasons for damage to the structural integrity of pipelines, as it can lead to loss of wall thickness. In this context, it is known that corrosion prevention and its prediction is crucial to ensure efficient pipeline operation (Zhou et al., 2016; Seghier, Höche & Zheludkevich 2022).

Therefore, this risk factor has been the object of study, as also seen in the work of Wasim & Djukic (2022), where a review of all external corrosion mechanisms in pipelines was carried out; and in the work of Zhou, Wu, Liu, Li & Qiao (2016), who estimated failure due to corrosion in oil and gas pipelines.

With regard specifically to internal corrosion, the corrosion rate depends on the operating pressure, the properties of the transported fluids and the injected inhibitors (Seghier, Höche & Zheludkevich 2022), with the mechanism of microbiological corrosion (MIC) being the major threat of internal corrosion in the oil pipeline, according to Askari et al (2019), citing Chevrot et al (2012) and Al-Saleh et al (2011).

Currently, monitoring systems for internal corrosion in pipelines can range from exposures of simple mass loss coupons (metallic test specimens) to corrosimetric probes that continuously provide material loss data. These are the conventional techniques that are characterized by the need for teams to travel to the places where the coupons and/or probes are installed in order to collect information for analysis, which implies time with team displacements and accident risks since they are invasive techniques.

This work, since data science can allow very powerful assistance tools for decision making (Seghier, Höche & Zheludkevich 2022), proposes a model developed in Fuzzy logic, structured in operational parameters of oil pumping, which helps in the evaluation of the phenomenon of internal corrosion in pipelines, whose predominant corrosion mechanism is microbiological, inferring its corrosivity potential.

2. Literature Revision

2.1 Pipelines and Mechanism of Internal Corrosion

Pipelines is the generic designation of installation consisting of pipes connected together, including components and complements, intended for the transport or transfer of fluids, between the borders of geographically distinct operating units (RTDT -ANP, 2011). Oil pipelines are modal efficient due to the advantages of transporting a large amount of product at a low cost. However, once failures in the structure of this pipeline occur, major accidents can occur, with leakage and consequent environmental contamination, (Kraidi et al, 2020).

Alamri (2020), in his research on localized corrosion, states that crude oil, as well as natural gas, generally carries many impurities that are corrosive in various circumstances. These impurities can include free water, hydrogen sulfide (H_2S) and carbon dioxide (CO_2), which expose the internal surfaces of oil and gas pipelines to corrosion damage.

Regarding the CO_2 mechanism, Olvera-Martínez et al (2015) state that, together with the H_2S corrosion mechanism, they are both well-known phenomena in the oil and gas industry, and are of particular importance in transport through steel pipelines. .

Regarding the H2S corrosion mechanism, the corrosion product in this case is iron sulfide (FeS) and the layer formed by this compound is cathodic in relation to the metallic wall of the pipeline, increasing the aggressiveness of the corrosive process, if its adherence show some instability. This aggressiveness, depending on the level of H2S saturation in the solution and the duct material being of low alloy, can cause the corrosivity to decrease over time (Li et al, 2022).

The mechanism of corrosion by O2, in oil pipelines, occurs when oil is contaminated with water. The presence of oxygen significantly increases the corrosivity of water and is the most critical point related to corrosion. This mechanism is characterized by the cathodic reduction of molecular O2 and the corrosion rate will depend on the cathodic reaction. Hence the importance of having a low BSW (basic sediment and water) value, which indicates the percentage of water (H2O) in oil.

Microbiologically Influenced Corrosion (MIC) is defined as corrosion influenced by the presence and activity of microorganisms, including bacteria and fungi, and usually promotes the form of pitting corrosion (Wei et al, 2022). Wei, in his work on microbiological corrosion in gas pipelines, quotes Javaherdashti et al (2008) who state that between 20-40% of failures in pipelines were due to internal microbiological corrosion.

Singh & Pokhrel (2017) stated that MIC is one of the degradation mechanisms in oil and gas pipelines and that, as with any corrosion process, predicting its onset is difficult to model accurately. Dawuda et al (2021) cites Litle & Lee (2007) who claim to be the prediction of microbiological corrosion, very challenging due to the complexity that involves the microbiological study in addition to the electrochemical reactions that involve the process.

Wang et al (2020), citing Olszewski (2007), state that MIC accelerates the corrosion rate of equipment and facilities, resulting in equipment failure and product loss, which is why MIC has become a focus of the oil industry. and gas. Wang et al (2020), also state that in relevant studies, it has been pointed out that MIC is mainly caused by bacteria, fungi and other anaerobic microorganisms, and that the sediment is an important induction. Therefore, prediction of solid particle deposition has become an important management measure for effective MIC prevention.

2.2 Management of Internal Corrosion in Pipelines

Corrosion management can be defined as a systematic way of measuring corrosion or degradation of equipment and installations, with the aim of helping to understand the corrosive process and/or obtaining useful information for controlling corrosion and its consequences (Magalhães, 2005).

With regard to internal corrosion, the most determining practice is largely based on the use of mass loss coupons and electrical resistance (ER) probes. There is even an implicit assumption that these are the only techniques available to assess metal loss due to corrosive conditions and that such instrumentation is 'standard' monitoring equipment (Cox, 2014).

The mass loss coupon (Figure 1) consists of a material sample placed in a specific corrosive medium to verify its behavior. In the coupon, the speed of development of the corrosive process - corrosion rate - is usually expressed by the variation of mass per unit of time. The corrosion rate is calculated based on the data obtained

from the mass loss coupon before its installation in the fitting room and after its removal.
To calculate the corrosion rate, equation 1, established by NACE (National Association Corrosion Engineers International) SP 0775-2018, is used.

$$T = \Delta m.\frac{365.1000}{S.t.d} \qquad (1)$$

where, T = corrosion rate (mm/year), Δm = mass loss (g), S = surface area of the exposed coupon (mm2), d = density (g/cm3), t = exposure time (days)

Electrical resistance probe is another technique for monitoring internal corrosion. It works by monitoring changes in the resistance of a thin sensing element, which is reduced in thickness due to corrosive action.
The method is based on the second Ohm equation, cited in equation 2:

$$R = \rho.\mathrm{l}.\frac{1}{A} \qquad (2)$$

where: R = resistance (ohm); l = length (cm); A = cross-sectional area (cm^2); □ = resistivity of the material (ohm.cm).
The (Figure 1) shows (A) a corrosion coupon and (B) an electrical resistance probe.

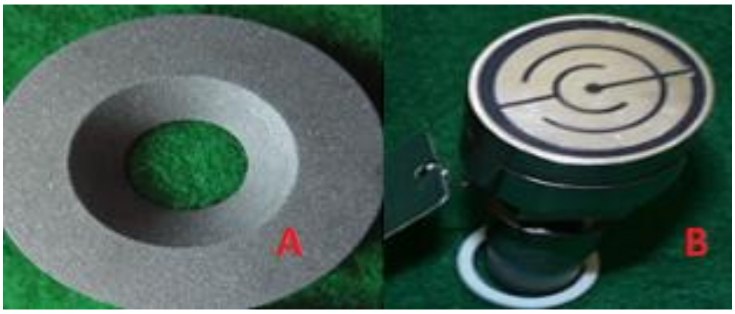

Figure 1 - (A) corrosion coupon and (B) electrical resistance probe

With the information obtained by monitoring techniques, those responsible for a pipeline will be able to make a better decision about the type, cost and urgency of corrective measures, such as corrosion inhibitors and pipeline cleaning using PIG (Pipelines Inspection Gauge) tools.).
In this context of corrosion management, corrosion inhibitors play an important role in controlling corrosion in all oil and gas production processes and, therefore, the research and development of suitable inhibitors in cost and efficiency is of great relevance and scope of several studies in recent decades (Da Silva, 2013).
Inhibitors can be of three types: cathodic, anodic and filmic, the latter, according to ASKARI et al (2021), in their technical review work on film-forming inhibitors, this type of inhibitor is rated the most economical and

reliable internal corrosion control method.

Another important element in mitigating corrosive mechanisms, in particular the MIC, are PIG's, the tool responsible for maintenance, inspection and internal cleaning of the pipeline. According to ZHOU et al (2022) there are several types of PIG's; and according to the work of LI et al (2021), in their analytical approach to the speed of PIG's in pipelines, the frequency of cleaning the pipeline with PIG promotes a considerable drag of condensate that eventually accumulates and that would favor the MIC.

(Figure 2) schematically illustrates a PIG cleaning the duct internally.

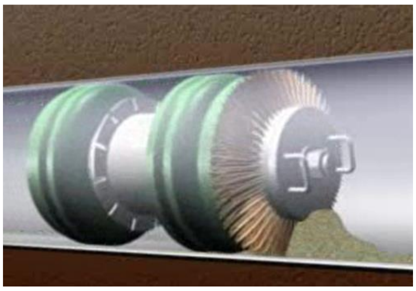

Figure 2 - Cleaning Pig

2.3 Structure of Fuzzy Logic

Fuzzy logic is based on the treatment of terms, mainly at the borders of sets, where there is doubt, uncertainty, about the pertinence of elements to a set (Nogueira, 2021).

A typical Fuzzy inference system is schematically presented in (Figure 3). This includes: (1) fuzzification, (2) knowledge base, (3) inference unit, and (4) defuzzification (Jamshidi et al, 2013).

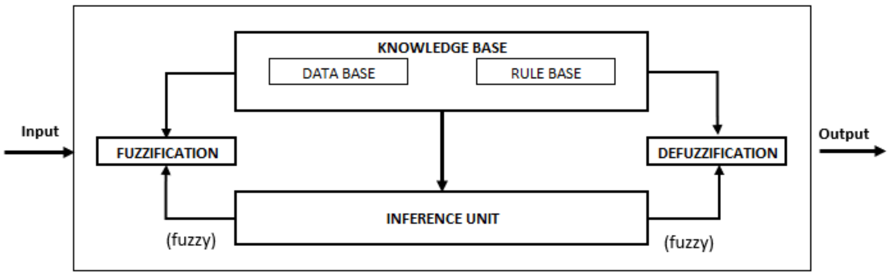

Figure 3 – Fuzzy inference system (Jamshidi et al, 2013)

2.3.1. Step 1: Fuzzification

Fuzzy sets for all variables are determined by membership functions. Using these functions, the sharp inputs can be converted to association values in the range of 0 to 1 (Zhou et al, 2016).

2.3.2. Step 2: Knowledge Base

Its purpose is to characterize the control strategy and the goals. In the database are stored the definitions of the Fuzzy sets that describe the predicates of each input variable (input parameters) and output (output parameter) with their respective membership functions which can be discrete or continuous. The rule base is formed by a set of Fuzzy rules that define the system control strategy.

Still regarding the rule base, known as "if-then" rules, we can say that they establish the relationship between inputs and outputs (input-output) of the Fuzzy model, and these rules are generally constructed by premises (also called antecedents) and conclusions (called consequents). For example: "if x is high (premise), then y is low (consequent)" (Jamshidi et al, 2013).

2.3.3. Step 3: Fuzzy Inference Unit

In the inference stage, the operations of the sets themselves occur, such as the combination of the antecedents of the rules of the type IF -THEN, generating the Fuzzy output set. (Nogueira, 2021)

There are several Inference Systems that have been applied in different aspects of science and engineering applications. The model (Mamdani, 1974) is one of the popular algorithms, and uses the concepts of Fuzzy sets and Fuzzy logic to translate a totally unstructured set into an algorithm.

The model (Mamdani,1974) will be used in this work.

2.3.4. Step 4: Defuzzyfication

In this step, the output Fuzzy set is finally converted into a crisp value. In general, the centroid method is used to calculate the final output value, which returns the center of gravity of the area under the membership function of the output set (Zhou et al, 2016).

3. Materials and Methods

3.1. Data

The data used to evaluate the Fuzzy model to be developed were obtained from the so-called monitoring "campaigns" that took place in the existing oil pipeline in the Amazon forest, which is 14 inches in diameter, 0.25 inches thick and 280 km long. extension, and has mass loss coupons and electrical resistance probes installed at km's 0.9, 35 and 278. The campaigns took place in the period between December 2021 and August 2022.

During the monitoring campaigns, in the first 3, only the mass loss technique by corrosion coupon was used; in the 4th campaign, the two conventional monitoring techniques were used, that is, by mass loss in corrosion coupon and by electrical resistance probe.

The choice of this pipeline as the object of study was due to the fact that it presents a predominantly microbiological internal corrosion mechanism, as attested by internal documents of the operating Company.

The method used in the development of the model to identify the corrosivity potential of the pipeline consisted of three steps: 1. Definition of operational parameters; 2. The Fuzzy model and its detailing; 3. Experiment of the proposed model.

3.2. Definition of Operating Parameters

Before defining the operational parameters to compose the model to be developed, it is necessary to present the internal standard of the pipeline operating company. Standard establishing criteria for monitoring and controlling internal Corrosion.

3.2.1. N-2785

It is the internal standard of the pipeline operating company, which establishes the rules for monitoring and controlling internal corrosion in its pipelines. This was prepared based on the criteria of the international standard NACE (THE NATIONAL ASSOCIATION OF CORROSION ENGINEERS) - SP 0775 - Preparation, Installation, Analysis, and Interpretation of Corrosion Coupons in Oilfield Operations.

N-2785 was based on NACE 0775, but adopted a difference when establishing the criteria for corrosivity potential, suppressing the concept of HIGH potential and adopting only the concepts of potential Low (LOW), Moderate (MODERATE) and Severe (SEVERE) .

Table 1 shows the difference in criteria between the N-2785 and NACE 0775 standards.

Table 1 - Difference in corrosivity potential NACE 0775 x N 2785

CORROSIVITY POTENTIAL			
NACE 0775		N-2785	
AVERAGE CORROSION RATE (mm/y)		UNIFORM RATE (COUPON/PROBE) (mm/year)	
< 0,025	LOW	< 0,025	LOW
0,025 a 0,12	MODERATE	0,025 a 0,125	MODERATE
0,13 a 0,25	HIGH	> 0,125	SEVERE
> 0,25	SEVERE		

3.2.2. Input and Output Operating Parameters

At this stage, the operational parameters for the composition of the model to be developed were defined in the N-2785 standard. For entry, 4 parameters were defined that are related to the control of the microbiological corrosion mechanism in the pipeline. They are: corrosion inhibitor injection in the oil pipeline, frequency of cleaning the pipeline with a PIG tool, oil flow rate in the pipeline and oil BSW (Basic Sediment and Water); the linguistic variables of the parameters were also defined

For the “output” of the model, the same criterion existing in the N-2785 standard was defined, that is, the corrosion rate determining the corrosivity potential.

3.2.3. Fuzzy Model

Using the Fuzzy Logic Toolbox™ of the MATLAB® software, the following steps for the formulation of the Mamdani-type Fuzzy inference model were: the elaboration of the Fuzzy rules – the model has 81 rules; and the fuzzification of inputs and definition of outputs.

The results obtained with the conventional techniques used during the campaigns were compared with the results obtained by the developed model.

The values of the operational parameters used in the model were those present during the campaigns. All this information was obtained from the Company operating the pipeline. (Figure 4) illustrates the implementation of the simulation model:

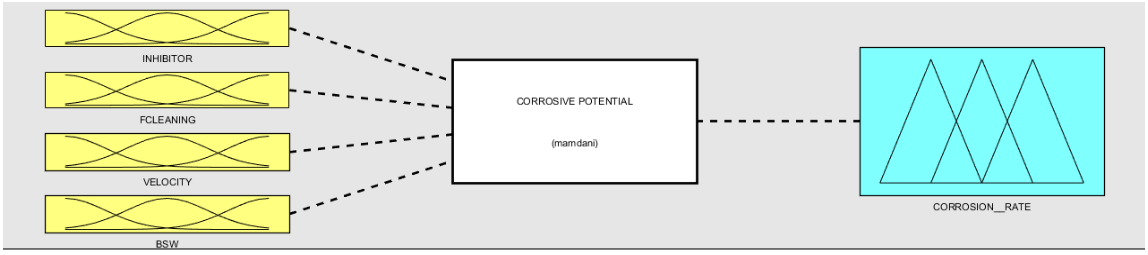

Figure 4- Input and output variables of the proposed model

System variables can be described as follows:

a) Corrosion Inhibitor (INHIBITOR): The ppm (part per million) of applied inhibitor is analyzed. For effective duct protection, it is recommended from 18 ppm (H-HIGH).

(Figure 5) illustrates that the fuzzification of this variable is the Trapezoidal function.

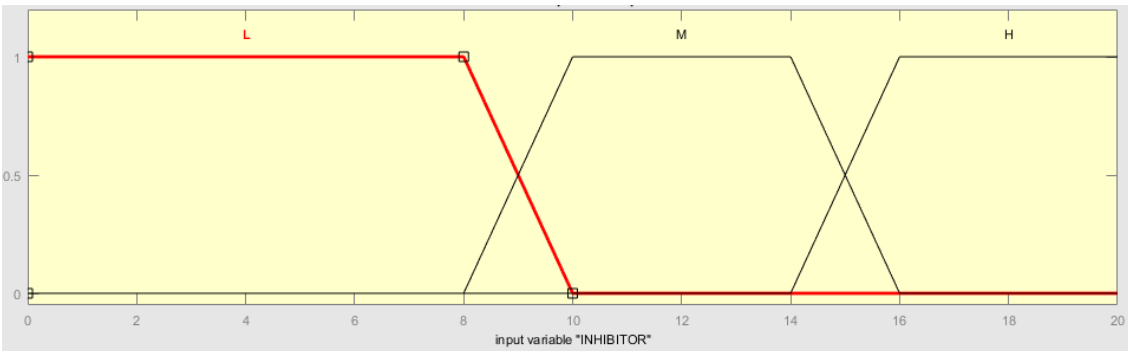

Figure 5 - Fuzzfication of the corrosion inhibitor variable (INHIBITOR)

b) Frequency of Cleaning (F. CLEANING): To promote effective cleaning (H-HIGH) in the duct, it is necessary 3 (three) “passages” of PIG in a period of 30 days.

(Figure 6) illustrates that the fuzzification of this variable is triangular.

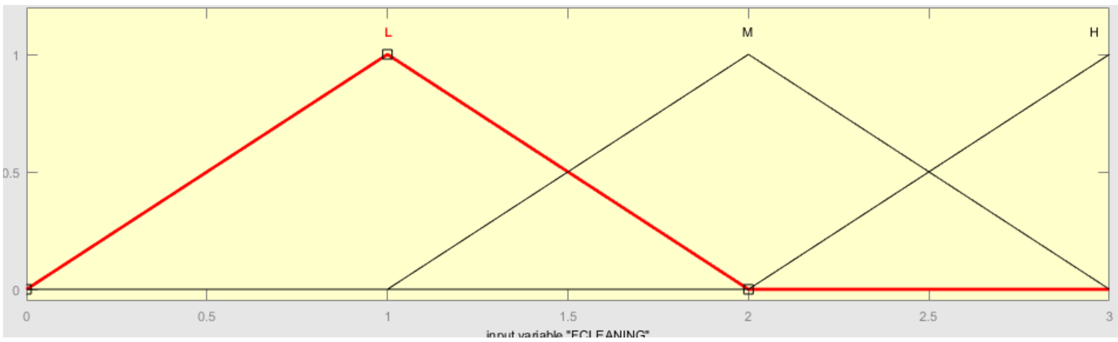

Figure 6 - Fuzzyfication of the cleaning frequency variable (FCLEANING)

c) Flow velocity (VELOCITY): A high velocity (H-HIGH) from 0.6 m/s was considered, so that there is drag of existing water in the pipeline.

(Figure 7) illustrates that the fuzzification of this variable is the Trapezoidal function.

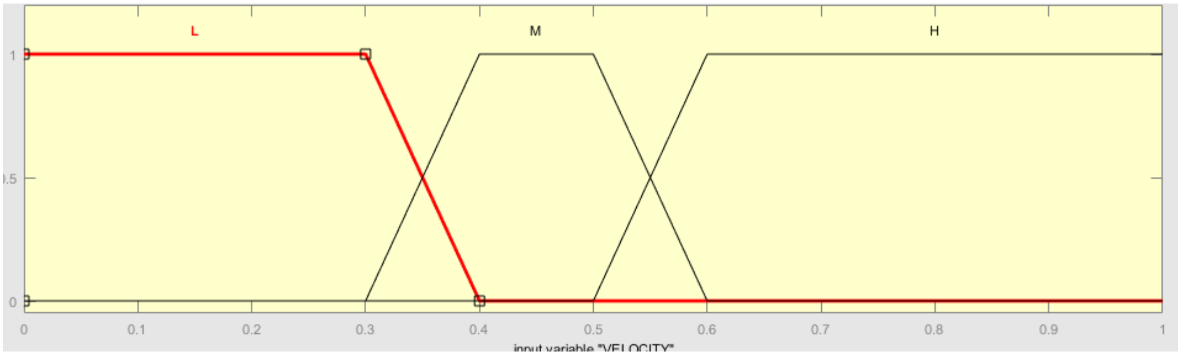

Figure 7 - Fuzzyfication of the velocity (VELOCITY)

d) Basic Sediment and Water (BSW): Below 15%, BSW does not favor corrosion, and we consider an L-LOW percentage. A percentage above 30% is H-HIGH, and greatly favors the decantation of water in the lower generatrix of the duct.

(Figure 8) illustrates that the fuzzification of this variable is the Trapezoidal function.

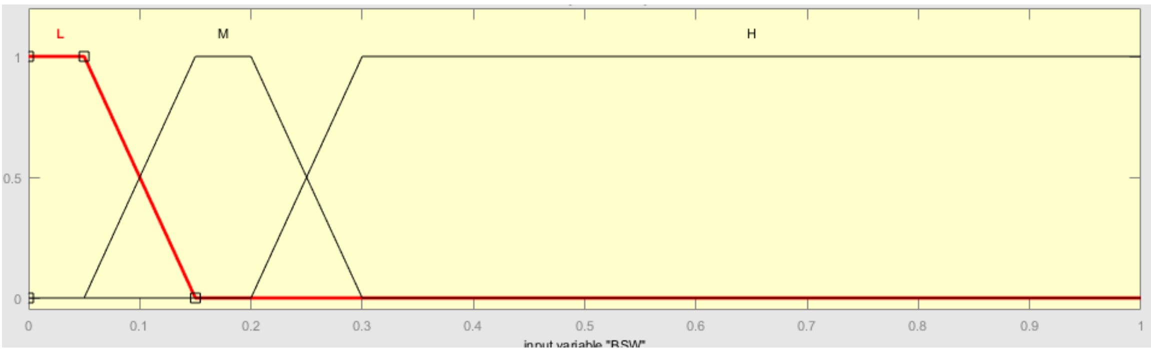

Figure 8 - Fuzzfication of the variable basic sediment and water (BSW)

For output variable, the model adopts the corrosion rate (CORROSION RATE) as it will define the existing corrosive potential in the pipeline.

We consider the criterion used in the internal standard N-2785 and (Figure 9) illustrates that the fuzzification of this variable is the Trapezoidal function.

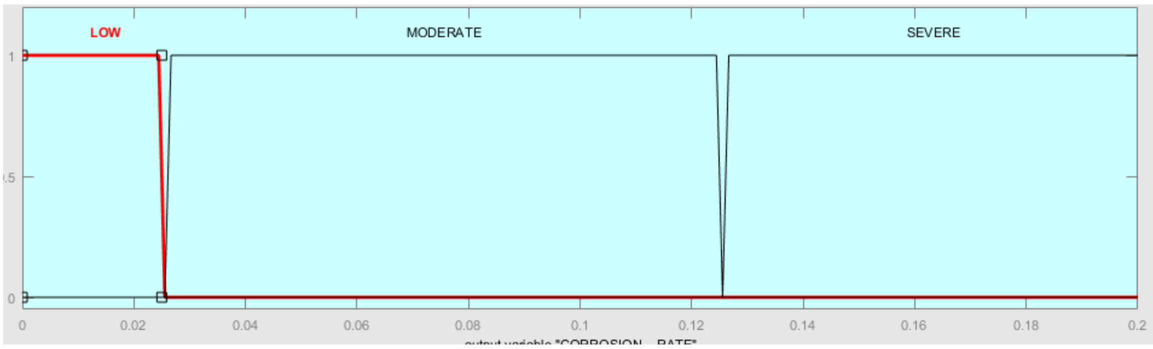

Figure 9 - Corrosion rate output variable fuzzfication (CORROSION RATE)

The rule base of linguistic variables resulted in 81 rules. Part can be observed in table 2.

Table 2 - Fuzzy Rules

1. If (INHIBITOR is L) and (FCLEANING is L) and (VELOCITY is L) and (BSW is L) then (CORROSION__RATE is SEVERE) (1)
2. If (INHIBITOR is L) and (FCLEANING is L) and (VELOCITY is L) and (BSW is M) then (CORROSION__RATE is SEVERE) (1)
3. If (INHIBITOR is L) and (FCLEANING is L) and (VELOCITY is L) and (BSW is H) then (CORROSION__RATE is SEVERE) (1)
4. If (INHIBITOR is L) and (FCLEANING is L) and (VELOCITY is M) and (BSW is L) then (CORROSION__RATE is MODERATE) (1)
5. If (INHIBITOR is L) and (FCLEANING is L) and (VELOCITY is M) and (BSW is M) then (CORROSION__RATE is SEVERE) (1)
6. If (INHIBITOR is L) and (FCLEANING is L) and (VELOCITY is M) and (BSW is H) then (CORROSION__RATE is SEVERE) (1)
7. If (INHIBITOR is L) and (FCLEANING is L) and (VELOCITY is H) and (BSW is L) then (CORROSION__RATE is MODERATE) (1)
8. If (INHIBITOR is L) and (FCLEANING is L) and (VELOCITY is H) and (BSW is M) then (CORROSION__RATE is SEVERE) (1)
9. If (INHIBITOR is L) and (FCLEANING is L) and (VELOCITY is H) and (BSW is H) then (CORROSION__RATE is SEVERE) (1)
10. If (INHIBITOR is L) and (FCLEANING is M) and (VELOCITY is L) and (BSW is L) then (CORROSION__RATE is LOW) (1)
11. If (INHIBITOR is L) and (FCLEANING is M) and (VELOCITY is L) and (BSW is M) then (CORROSION__RATE is LOW) (1)
12. If (INHIBITOR is L) and (FCLEANING is M) and (VELOCITY is L) and (BSW is H) then (CORROSION__RATE is MODERATE) (1)
13. If (INHIBITOR is L) and (FCLEANING is M) and (VELOCITY is M) and (BSW is L) then (CORROSION__RATE is LOW) (1)
14. If (INHIBITOR is L) and (FCLEANING is M) and (VELOCITY is M) and (BSW is M) then (CORROSION__RATE is LOW) (1)
15. If (INHIBITOR is L) and (FCLEANING is M) and (VELOCITY is M) and (BSW is H) then (CORROSION__RATE is MODERATE) (1)
16. If (INHIBITOR is L) and (FCLEANING is M) and (VELOCITY is H) and (BSW is L) then (CORROSION__RATE is LOW) (1)
17. If (INHIBITOR is L) and (FCLEANING is M) and (VELOCITY is H) and (BSW is M) then (CORROSION__RATE is MODERATE) (1)

4. Resultados E Discussões

Table 3 presents the corrosion rate results and consequent corrosivity potential in the pipeline, obtained in the monitoring campaigns using the conventional monitoring techniques employed.

Table 3 - Results of monitoring campaigns

MONITORING PERIOD (CAMPAIGN)	MONITORING TECHNIQUE	PIPE LINE KM	CORROSION RATE (mm/year)	CORROSIVITY POTENTIAL
CAMPAIGN 1 - december 2021	MASS LOSS COUPON	**0.900**	0,008	LOW
		35	0,001	LOW
		278	0,003	LOW
CAMPAIGN 2 - april 2022	MASS LOSS COUPON	**0.900**	0,030	MODERATE
		35	0,026	MODERATE
		278	0,029	MODERATE
CAMPAIGN 3 - july 2022	ELECTRICAL RESISTANCE PROBE	**0.900**	0,014	LOW
		35	0,002	LOW
		278	0,032	MODERATE
CAMPAIGN 4 - august	MASS LOSS COUPON	**0.900**	0,021	LOW
		35	0,013	LOW
		278	0,016	LOW

2022	**ELECTRICAL RESISTANCE PROBE**	**0.900**	0,014	LOW
		35	0,002	LOW
		278	0,023	LOW

Table 4 presents the inference values, obtained using the model developed in Fuzzy logic, using as input data, the operational parameters present during the monitoring campaigns.

Table 4 - Values obtained with Fuzzy Model

MONITORING PERIOD (CAMPAIGN)	**INPUT PARAMETERS**		**CORROSION RATE (mm/year)**			**CORROSIVITY POTENTIAL**
	INPUT		**km 0.9**	**km 35**	**km 278**	***OUTPUT***
CAMPAIGN 1 - december 2021	**INHIBITOR (PPM)**	15	0,012			LOW
	FREQ.CLEANING (pig)	2				
	VELOCITY (m/s)	0,45				
	BSW (%)	0,05				
CAMPAIGN 2 - april 2022	**INHIBITOR (PPM)**	0	0,100			MODERATE
	FREQ.CLEANING (pig)	0				
	VELOCITY (m/s)	0,22				
	BSW (%)	0,05				
CAMPAIGN 3 - July 2022	**INHIBITOR (PPM)**	15	0,062			MODERATE
	FREQ.CLEANING (pig)	1				
	VELOCITY (m/s)	0,14				
	BSW (%)	0,05				
CAMPAIGN 4 - august 2022	**INHIBITOR (PPM)**	20	0,012			LOW
	FREQ.CLEANING (pig)	2				

	VELOCITY (m/s)	0,3		
	BSW (%)	0,05		

When we combine a high ppm inhibitor application with a higher number of PIG passes, the lower the corrosion rate.

In the graph (Figure 10) we see the corrosion rate variation when we modify the ppm of the corrosion inhibitor and the number of frequency of cleanings (PIG). A higher frequency of cleaning (PIG) number associated with a higher level of inhibitor application tends to reduce the corrosion rate.

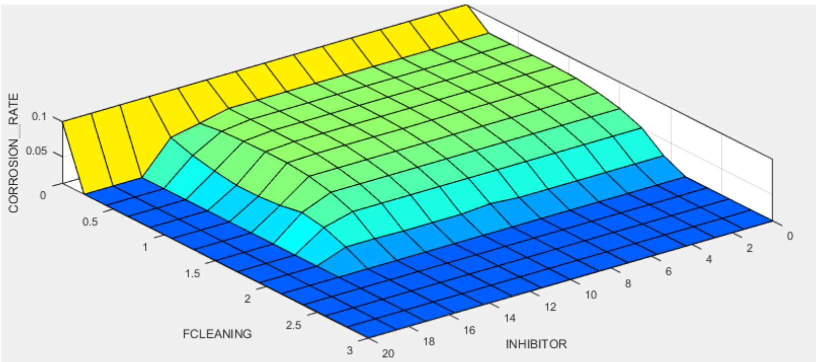

Figure 10 - Graph of the corrosion rate linguistic variable

In the graph (Figure 11) we see the variation in the corrosion rate when we modify the flow velocity and there are variations in the BSW. With a higher flow velocity, associated with a low BSW, the corrosion rate tends to decrease.

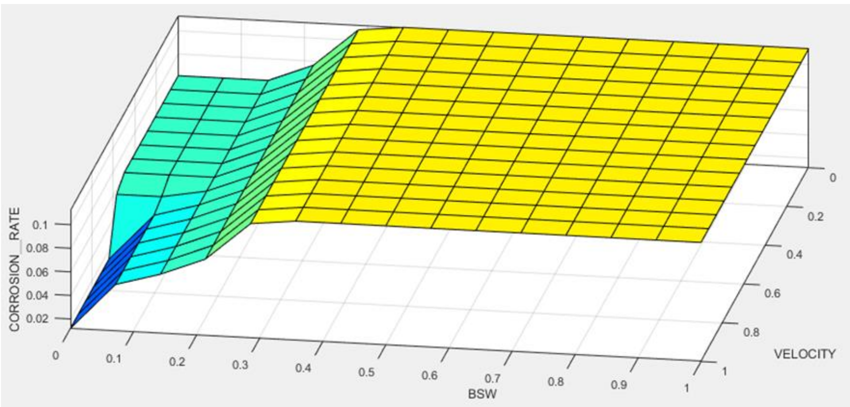

Figure 11 – Graph of the linguistic variable velocity

(Figure 12) presents the inference result for the 4th campaign, considering the operational parameters seen in table 4.

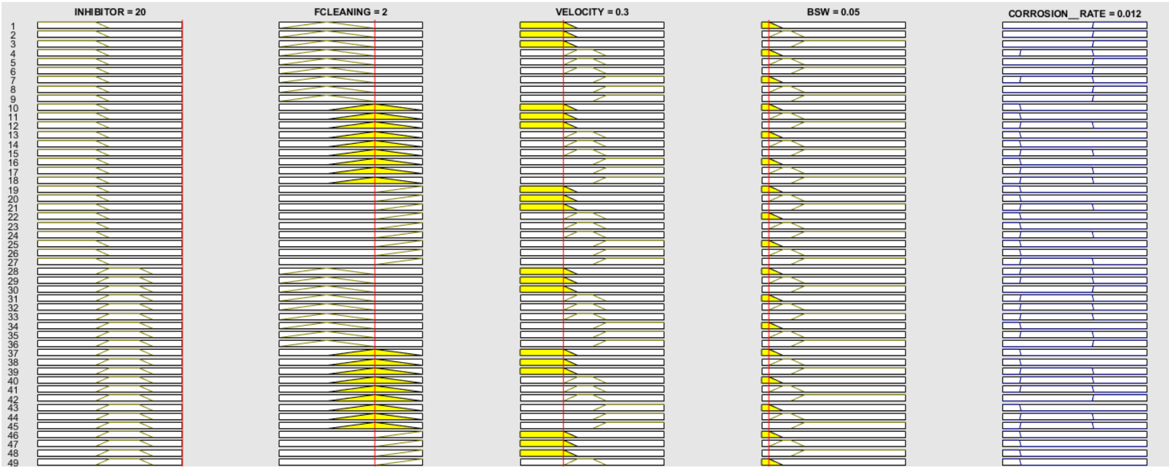

Figure 12 - Inference Result for 4th Campaign

Table 5 presents a comparative table of the results obtained by conventional techniques for monitoring internal corrosion, with the results inferred by the developed Fuzzy model.

Table 5 - Comparison of conventional techniques x Fuzzy model

Monitoring period (CAMPAIGN)	**MONITORING TECHNIQUE**	**PIPELINE KM**	**CORROSION RATE (MM/YEAR)**		**CORROSIVITY POTENTIAL - N2785**	
			MONITORING TECHNIQUE	**FUZZY MODEL**	**MONITORING TECHNIQUE**	**FUZZY MODEL**
CAMPAIGN 1 - December 2021	MASS LOSS COUPON	0.900	0,008	0,012	LOW	LOW
		35	0,001		LOW	
		278	0,003		LOW	
CAMPAIGN 2 - April 2022	MASS LOSS COUPON	0.900	0,030	0,100	MODERADO	MODERATE
		35	0,026		MODERADO	
		278	0,029		MODERADO	
CAMPAIGN 3 - july 2022	RESIST. PROBE ELECTRICAL	0.900	0,014	0,062	LOW	MODERATE
		35	0,002		LOW	
		278	0,032		MODERATE	
CAMPAIGN 4 - August 2022	MASS LOSS COUPON	0.900	0,021	0,012	LOW	LOW
		35	0,013		LOW	
		278	0,016		LOW	
CAMPAIGN 4 - August 2022	RESIST. PROBE ELECTRICAL	0.900	0,014	0,012	LOW	LOW
		35	0,002		LOW	
		278	0,023		LOW	

The 04 (four) internal corrosion monitoring campaigns, using conventional techniques, resulted in 15 results of corrosion rate and, consequently, 15 results of potential corrosivity acting in the pipeline, each result corresponding to a certain moment and region of the duct.

The model developed in Fuzzy logic, after the input of the operational data considered, in each of the respective campaigns, presented results of corrosivity potential equal to 13 of those results obtained by conventional techniques. Considering the great difficulty in being able to infer absolute values, it is possible to attest to the relevance of the model when there is 86% agreement with the results of the corrosivity potential. When we compare the results of the Fuzzy model with each of the techniques, separately, the model had 100% of correct answers when compared to the internal corrosion monitoring technique using a mass loss coupon; and 66.7% of correct answers with the electrical resistance probe monitoring technique.

As for the values of the corrosion rates obtained by the Fuzzy logic model, it is possible to verify that only in campaign 4, in 5 (five) measurements of the 6 (six) carried out, these corrosion rates were lower than the corrosion rates obtained with the conventional techniques. For the other campaigns, the values obtained by the developed model were higher than the values found by conventional techniques. That is, the developed model is conservative.

As the work LI et al (2021) stated, the frequency of cleaning (PIG) is in fact very relevant for the elimination of condensate, thus disfavoring the formation of bacterial colonies that could promote the mechanism of microbiological corrosion. The results show that 2 (two) PIG passes already contribute to LOW corrosivity potential.

As the work of ASKARI et al (2021) stated, the use of inhibitor actually promotes greater corrosion control. The results showed that, in fact, the use of the inhibitor keeps the corrosivity potential at LOW levels.

5. Conclusion

The developed model proved to be viable as a proposal for monitoring the corrosivity potential, in a pipeline whose corrosion mechanism is predominantly due to the microbiological corrosion mechanism.

The input variables adopted (corrosion inhibitor, cleaning frequency with PIG tool, flow rate and BSW), as well as their membership functions, proved to be adequate to the model as it allowed the output variable to be very close to the actual values obtained by the monitoring methods.

Corrosion inhibitor parameters and frequency of cleaning with PIG, when combined, proved to be decisive for controlling corrosion at LOW potential levels, especially when the evaluations were made in relation to the results due to loss of mass in the corrosion coupon. This is well confirmed in campaign 2, when these parameters were not adequate.

The model developed in Fuzzy logic was completely assertive when its results of potential corrosivity of the pipeline are compared to the results obtained in the campaigns carried out using the monitoring technique by mass loss coupons.

To define the corrosivity potential, the model developed in Fuzzy logic had a small disagreement in its corrosion rate values in relation to those obtained by the electrical resistance probe technique, especially in campaign 3, which led to a different definition between technique and model. This small divergence, however,

does not make the model unfeasible, since the model defined a more critical potential.
The model developed in Fuzzy logic is conservative. That is, predominantly, the model always infers a higher corrosion rate than the existing one. Even when it presented a lower rate than those found in measurements by conventional techniques, the results were very close to the values found by those techniques

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