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A Fuzzy Logic Model Designed for Quantitative Risk Analysis based on ECDA Data

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ABSTRACT

Describes a fuzzy logic model intended for quantitative risk analysis to the integrity of buried pipelines. The proposed approach correlates data from combined CIPS+DCVG coating surveys to the soil resistivity, in order to define an indicator that expresses the corrosion susceptibility at a given coating defect location. Inputs used in the mathematical model include: DCVG defect severity, CIPS pipe-to-soil "OFF" potentials and local soil electrical resistivity. The output is a real number, defined in the interval [0, 3], which provides a qualitative and quantitative degree of steel exposure to corrosion activity. Easy to implement, the presented method is an additional tool to assist pipeline operators with assessing the condition of their pipelines and prioritizing corrective actions.

Key words: fuzzy logic, pipeline integrity, soil corrosivity, cathodic protection, DCVG, ECDA.

INTRODUCTION

Corrosion is recognized as the most important contributing factor to pipeline failure. Corrosion is likely to occur at locations where coating defects exist and cathodic protection levels are insufficient. The defect exposes the unprotected steel to the surrounding soil (electrolyte), whose aggressiveness is characterized by several parameters related to its physical and chemical properties.

NACE establishes a methodology for External Corrosion Direct Assessment – ECDA in the standard SP0502-2002 [1], which constitutes a structured and proactive process aimed towards the integrity of pipelines. This process includes prevention of threats, identification of anomalies, corrosion activity assessment and corrective actions.

The SP0502-2002 ECDA methodology requires that at least two different indirect inspection techniques must be employed for integrity surveys. Any indications of concern must be analyzed along with environmental parameters that may expose the structure to corrosive activity, such as: electrical resistivity, moisture, pH, soil composition, presence of SRB etc. Based on this data, associated with pipeline history and specific operator's criteria, priorities are defined for direct inspections (excavations) and repairs.

Two of the most widely employed indirect inspection methods are DCVG – Direct Current Voltage Gradient and CIPS – Close Interval Potential Survey. Each of these techniques has specific criteria for characterizing indications, ranking anomalies and defining corrective measures [2]. Currently, there are instruments available that allow for the combination of both techniques (CIPS+DCVG) [3], providing a complete, ECDA compliant set of indirect inspection data. Accuracy of the data is improved because the two surveys are carried out simultaneously at the same geographic point, in the same conditions, with the same equipment, by the same surveyor and without additional cost.

It is known that the cost for excavating, analyzing and repairing sections of pipe is often the most expensive step of the overall ECDA process. To define priorities for corrective actions is a complex task and of great responsibility. It requires experience of the operator and the simultaneous analysis of multiple variables, with several classification criteria. If priorities are determined without a consistent method, the pipeline operator is subject to the risk of: 1) waste of time and resources with low priority (or even unnecessary) interventions; and 2) not knowing if all necessary corrective measures were performed in order to ensure the pipeline integrity.

This paper proposes a fuzzy logic model to evaluate the variety of ECDA data in a consistant manner. The concept of fuzzy logic was introduced by L. A. Zadeh [4], to address the vague aspect of information. It is considered one of the most well succeeded [5] approaches for handling complex engineering problems, especially when a mathematical model is subject to uncertainties. Recently, fuzzy logic has been applied successfully to innumerous problems of environmental and civil engineering, including modelling of pipeline deterioration [6] and evaluation of soil corrosivity [7].

The fuzzy model proposed correlates data from combined CIPS+DCVG surveys to the soil resistivity. Inputs are: DCVG defect severity (IR%), CIPS pipe-to-soil "OFF" values, potential dips with respect to the profile and local soil electrical resistivity. The output is a real number, named "Priority Index", defined in the interval [0, 3], which quantifies numerically the degree of risk of corrosion activity at a given defect location. The presented method may provide a complementary indicator to assist pipeline operators with assessing the condition of their pipeline and prioritizing corrective actions.

DESCRIPTION OF THE MATHEMATICAL MODEL

The proposed method uses membership functions to map each of the input parameters to the anomaly classes given under NACE SP0502-2002 as listed below [8]:

- Severe – indications that the pipeline operator considers as having the highest likelihood of corrosion activity.
- Moderate – indications that the pipeline operator considers as having possible corrosion activity.
- Minor – indications that the pipeline operator considers inactive or as having the lowest likelihood of corrosion activity.

The general form of the membership functions is presented in equations (1) to (3), expressed in terms of an argument x:

$$\mu_S(x) = \begin{cases} \left(\dfrac{ax + bx_1}{|x_2 - x_1|}\right)^k; & x_1 < x < x_2 \\ c\,; & x \le x_1 \\ 1 - c\,; & x \ge x_2 \end{cases} \quad (1)$$

$$\mu_{Mo}(x) = 1 - \mu_S(x) - \mu_{Mi}(x) \quad (2)$$

$$\mu_{Mi}(x) = \begin{cases} \left(\dfrac{-ax - bx_1}{|x_4 - x_3|}\right)^k; & x_3 < x < x_4 \\ 1 - c\,; & x \le x_3 \\ c\,; & x \ge x_4 \end{cases} \quad (3)$$

In which μ_S, μ_{Mo} and μ_{Mi} are the fuzzy numbers representing membership degrees of a given parameter (or anomaly) μ to the Severe, Moderate and Minor indication sets, respectively. Constants a, b, c and k are assigned heuristically to shape transitions between membership degrees. Values x_1, x_2, x_3 and x_4 are the boundary values of each severity class, dependent on the parameter's ranking scheme. Membership values range from 0 to 1.

The constants used to build the fuzzy numbers to evaluate DCVG indications, pipe-to-soil "OFF" potentials, potential dips and soil resistivity are summarized in Table 1. Values were chosen in accordance with each parameter's corrosivity criteria, as described in Tables 2 to 5. Membership functions results are illustrated in Figure 1.

Table 1: Parameters and constants of the fuzzy logic model

Parameter	Function	a	b	x_1	x_2	x_3	x_4	c	k
DCVG indication – IR%	$\mu_{IR\%}$	1,0	-1,0	45,0	51,0	23,0	35,0	0,0	1,0
CIPS pipe-to-soil "OFF" potential (mV)	μ_{CP}	1,0	-1,0	-700,0	-650,0	-900,0	-850,0	0,0	1,0
CIPS pipe-to-soil "OFF" potential (mV)	μ_{OP}	-1,0	1,0	-1200,0	-1100,0	-1100,0	-950,0	1,0	1,0
Potential dip (mV)	μ_D	1,0	-1,0	80,0	100,0	30,0	50,0	0,0	1,0
Soil resistivity (Ω.cm)	μ_ρ	-1,0	1,0	2000,0	2500,0	9500,0	10000,0	1,0	1,0

Table 2: DCVG Severity Classification (NACE TG-294)

Category	IR%
A	71 to 100
B	36 to 70
C	16 to 35
D	1 to 15

Table 3: CIS Indication Severity Classification as in [8]

Category	Potential Dip (mV)
Severe	> 100
Moderate	50 to 100
Minor	< 50

Table 4: Cathodic Protection Criteria for soils without SRB (NACE RP-0169 [10])

Description	"OFF" Potential (mV)
Steel and Cast Iron	Equal or more electronegative than -850 mV @ $Cu/CuSO_4$
Limit for overprotection	More electronegative than -1200 mV @ $Cu/CuSO_4$

Table 5: Soil classification based on electrical resistivity [11]

Soil corrosivity	Resistivity (Ω.cm)
Extremely corrosive	0 to 500
Very corrosive	500 to 1000
Corrosive	1000 to 3000
Moderately corrosive	3000 to 10000
Slightly corrosive	10000 to 25000
Not corrosive	> 25000

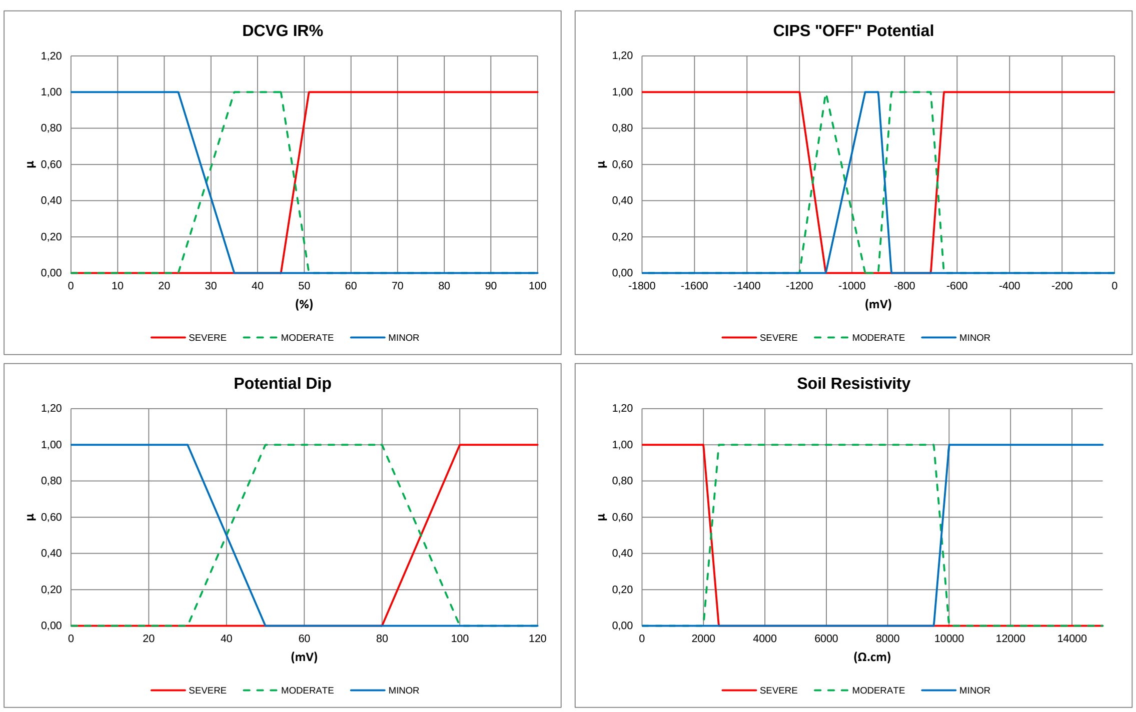

Figure 1: Membership functions of the fuzzy model

The weighting scheme follows the Analytic Hierarchy Process (AHP) proposed by *Saaty et al* [9], to estimate the relative importance of each variable (IR%, "OFF" potentials, potential dips and soil resistivity) based on pair-wise comparisons. The relative importances of different parameters were assigned using intensity of importance as described in Table 6.

Table 6: Intensities of importance under the AHP

Intensity of importance	Definition
1	Equal importance
3	Weak importance
5	Strong importance
7	Demonstrated importance
9	Absolute importance
2, 4, 6, 8	Intermediate values

An auxiliary importance matrix $\boldsymbol{A}$ was built, such that each element A_{ij} in the upper triangular matrix expresses the importance intensity of a variable i with respect to another variable j. Each element in the lower triangle of the matrix is the reciprocal of upper triangle, i.e. $A_{ij} = 1/A_{ji}$. The value of each element A_{ij} should be assigned based on specialists' judgment, pipeline history, field conditions and specific criteria determined by the pipeline operator. The authors propose, as a first approach, the importance matrix below:

$$\boldsymbol{A} = \begin{array}{c} \begin{array}{ccccc} \mu_{IR\%} & \mu_{CP} & \mu_{OP} & \mu_{D} & \mu_{\rho} \end{array} \\ \begin{bmatrix} 1 & 2 & 8 & 8 & 7 \\ 0,5 & 1 & 8 & 8 & 7 \\ 0,13 & 0,13 & 1 & 9 & 7 \\ 0,13 & 0,13 & 0,11 & 1 & 7 \\ 0,14 & 0,14 & 0,14 & 0,14 & 1 \end{bmatrix} \end{array} \begin{array}{c} \\ \mu_{IR\%} \\ \mu_{CP} \\ \mu_{OP} \\ \mu_{D} \\ \mu_{\rho} \end{array} \tag{4}$$

Importance intensities A_{ij} can be modified as required, if better information becomes available. A matrix $\boldsymbol{I}$ can be determined by normalizing matrix $\boldsymbol{A}$ column wise. The weight vector $\boldsymbol{I'}$ is obtained by taking the summation of the elements of each row of the normalized matrix $\boldsymbol{I}$ [7].

$$\boldsymbol{I} = \begin{bmatrix} 0,5283 & 0,5895 & 0,4637 & 0,3060 & 0,2414 \\ 0,2642 & 0,2947 & 0,4637 & 0,3060 & 0,2414 \\ 0,0660 & 0,0368 & 0,0580 & 0,3443 & 0,2414 \\ 0,0660 & 0,0368 & 0,0064 & 0,0383 & 0,2414 \\ 0,0755 & 0,0421 & 0,0083 & 0,0055 & 0,0345 \end{bmatrix} \rightarrow \boldsymbol{I'} = \begin{bmatrix} 2,1288 \\ 1,5699 \\ 0,7465 \\ 0,3890 \\ 0,1658 \end{bmatrix} \tag{5}$$

The final weight vector $\boldsymbol{W}$ is obtained by normalizing $\boldsymbol{I'}$ and taking the transpose, as below:

$$\boldsymbol{W} = [w_{IR\%} \quad w_{CP} \quad w_{OP} \quad w_{D} \quad w_{\rho}] = [0.4258 \quad 0.3140 \quad 0.1493 \quad 0.0778 \quad 0.0332] \tag{6}$$

The above weight vector $\boldsymbol{W}$ indicates that based on pair-wise importance selected above, DCVG IR% has the most influence on the outcome, while soil resistivity has the least. This apparent bias is in accordance with the fact that the IR% is the positive information that establishes the presence of a coating defect itself and, therefore, the need of repairs. The other parameters (pipe-to-soil potentials, dips and soil resistivity) are related to how the exposed steel interact with the electrolyte, providing complementary information about the defect's severity.

Equations (1) to (3) establish membership values used to set up an auxiliary matrix $\boldsymbol{M}$, in which rows represent membership values corresponding to each one of the three indication classes (Severe, Moderate, Minor) for IR% value, pipe-to-soil "OFF" potential, potential dip and soil resistivity. The weight vector $\boldsymbol{W}$ is then multiplied by $\boldsymbol{M}$ to define the fuzzy evaluation matrix $\boldsymbol{F}$:

$$\boldsymbol{F} = \boldsymbol{W} \times \boldsymbol{M} = [w_{IR\%} \quad w_{CP} \quad w_{OP} \quad w_D \quad w_\rho] \times \begin{bmatrix} \mu_{S-IR\%} & \mu_{Mo-IR\%} & \mu_{Mi-IR\%} \\ \mu_{S-CP} & \mu_{Mo-CP} & \mu_{Mi-CP} \\ \mu_{S-OP} & \mu_{Mo-OP} & \mu_{Mi-OP} \\ \mu_{S-D} & \mu_{Mo-D} & \mu_{Mi-D} \\ \mu_{S-\rho} & \mu_{Mo-\rho} & \mu_{Mi-\rho} \end{bmatrix} = [m_S \quad m_{Mo} \quad m_{Mi}] \tag{7}$$

In equation (7), m_S, m_{Mo} and m_{Mi} are the fuzzy numbers expressing the overall membership degrees to the Severe, Moderate and Minor indication classes, respectively.

In order to effectively assess an anomaly's severity scale, fuzzy numbers have to be converted to crisp values, a step known as *defuzzyfication*. This is accomplished by using the maximum operator to determine severity classification membership from matrix $\boldsymbol{F}$:

$$R_P = \max(m_S \quad m_{Mo} \quad m_{Mi}) \tag{8}$$

The crisp number R_P expresses, therefore, the overall dominant characteristic of the indication severity level. Since it is desirable to have a unique real number to allow for ranking and comparisons between distinct anomalies, it is defined the Priority Index P as:

$$P = \begin{cases} 1 - m_S ; & \forall\, R_P = m_S \\ 1 + (1 - m_{Mo}) ; & \forall\, R_P = m_{Mo} \\ 2 + (1 - m_{Mi}) ; & \forall\, R_P = m_{Mi} \end{cases} \tag{9}$$

The Priority Index ranges from 0 to 3, as described in Table 7, and is modeled to sort any given set of anomalies in descending order of priority (or severity), i.e. zero corresponds to the most severe anomaly, whilst a value of three represents the least severe indication of the data set. This ranking scheme may seem counterintuitive at first, but it brings the advantage of sorting groups of defects as usually found in pipeline surveys, in the precise order of how excavations and repairs should be executed.

Table 7: Priority Index Severity Classification

Category	P
Severe	0 to 1
Moderate	1 to 2
Minor	2 to 3

RESULTS AND DISCUSSION

Data from a combined CIPS+DCVG survey of a real pipeline are used to validate the fuzzy model. Measurements of IR%, “OFF” potential, potential dip and soil resistivity were performed at defect locations over an extension of approximately 15 km. For each indication, measured parameters are classified individually, in accordance with the criteria presented in Tables 2 to 5. Then, the Priority Index is computed and the overall severity class evaluated based on Table 7. The process was repeated for 25 coating defect samples.

Results are presented in descending order of priority in Table 8 and Figure 2. Values of the chart are normalized with respect to 3 in order to fit all the information into the same scale. Markers represent field measurements, horizontal lines indicate reference values for each variable accounted for. The pipe-to-soil axis is not inverted.

Table 8: Fuzzy Model results for DCVG, CIPS and resistivity data for 25 coating defects

DEFECT #	IR%	DCVG Class.	OFF (mV)	CIPS Class.	Dip (mV)	Dip Class.	ρ (Ω.cm)	Resistivity Class.	P	Overall Class.
1	56.15	B	-688.00	Unprotected	341.20	Severe	199760.87	Not corrosive	0.421087	**Severe**
2	78.29	A	-1172.00	Protected	38.20	Minor	298623.26	Not corrosive	0.466742	**Severe**
3	56.70	B	-797.00	Unprotected	230.40	Severe	7329.99	Moderately corrosive	0.496444	**Severe**
4	51.75	B	-817.00	Unprotected	80.00	Moderate	360412.26	Not corrosive	0.574235	**Severe**
5	38.40	B	-817.00	Unprotected	232.80	Severe	4626.72	Moderately corrosive	1.227086	**Moderate**
6	44.52	B	-742.00	Unprotected	342.80	Severe	71741.80	Not corrosive	1.260247	**Moderate**
7	43.88	B	-693.00	Unprotected	288.80	Severe	270560.76	Not corrosive	1.304205	**Moderate**
8	32.88	C	-777.00	Unprotected	218.40	Severe	306121.62	Not corrosive	1.335465	**Moderate**
9	46.47	B	-835.00	Unprotected	141.60	Severe	192085.52	Not corrosive	1.364559	**Moderate**
10	46.55	B	-835.00	Unprotected	169.80	Severe	249401.25	Not corrosive	1.370236	**Moderate**
11	31.81	C	-782.00	Unprotected	204.00	Severe	485792.43	Not corrosive	1.373429	**Moderate**
12	31.00	C	-822.00	Unprotected	180.00	Severe	171231.73	Not corrosive	1.402168	**Moderate**
13	37.27	B	-1107.00	Protected	35.40	Minor	282468.02	Not corrosive	1.414386	**Moderate**
14	35.79	B	-880.00	Protected	189.00	Severe	517684.56	Not corrosive	1.448639	**Moderate**
15	28.57	C	-815.00	Unprotected	214.80	Severe	369954.15	Not corrosive	1.488386	**Moderate**
16	27.96	C	-859.00	Protected	75.60	Moderate	112725.28	Not corrosive	1.488757	**Moderate**
17	35.64	B	-887.00	Protected	166.80	Severe	387654.13	Not corrosive	1.492598	**Moderate**
18	28.34	C	-768.00	Unprotected	271.00	Severe	330740.67	Not corrosive	1.496546	**Moderate**
19	28.30	C	-804.00	Unprotected	150.60	Severe	490008.24	Not corrosive	1.497966	**Moderate**
20	36.43	B	-959.00	Protected	84.00	Moderate	353654.09	Not corrosive	1.503045	**Moderate**
21	27.80	C	-817.00	Unprotected	153.60	Severe	287568.83	Not corrosive	1.515706	**Moderate**
22	5.31	D	-943.00	Protected	28.80	Minor	470715.27	Not corrosive	2.000000	**Minor**
23	8.02	D	-945.00	Protected	6.40	Minor	58531.18	Not corrosive	2.000000	**Minor**
24	7.94	D	-921.00	Protected	8.60	Minor	379013.32	Not corrosive	2.000000	**Minor**
25	7.95	D	-914.00	Protected	29.80	Minor	116764.09	Not corrosive	2.000000	**Minor**
25	7.95	D	-914.00	Protected	29.80	Minor	116764.09	Not corrosive	2.000000	**Minor**

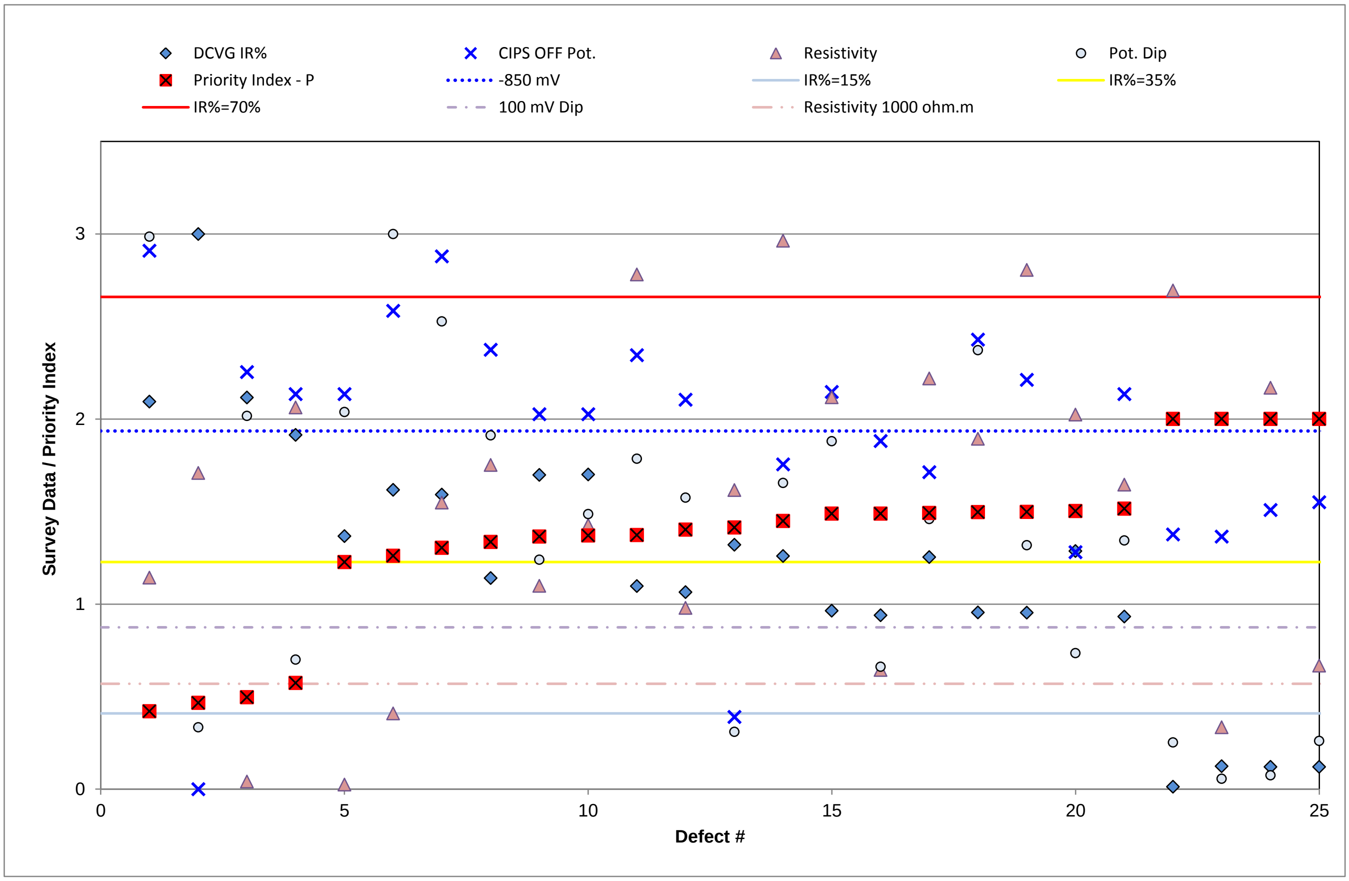

Figure 2: Priority Index and field data for 25 coating defects

The figure illustrates how complex, if not impossible, is to extract conclusions from multi-criteria analysis solely based on the superposition of field measurements for each indication. One can categorize coating defects based on IR%, identify poor cathodic protection levels, large potential dips, corrosive soil regions etc. by assessing each parameter individually, but only on an intuitive basis. A systematic approach arises when inputs are merged into a single outcome, as shown by the red markers on chart above: it is possible to notice a growing trend, with defects distributed into three clear levels, corresponding to the Severe, Moderate and Minor overall classes.

Analysis of the table and figure above shows that the highest IR% indications, dips and pipe-to-soil potentials (below criterion) yield the most severe overall indications, as expected. There is a complementary behavior between the IR% and the "OFF" potential in the resulting priority value. Potential dip and soil resistivity perform as "tie breakers" when anomalies have similar characteristics.

In order to analytically measure how parameters affect the model's response, Pearson's correlation coefficients with respect to Priority Index P were evaluated and are presented below:

Table 9: Pearson's Correlation between P and input parameters

Parameter	k=
DCVG IR%	-0.93
CIPS "OFF" Potential	-0.25
Potential Dip	-0.57
Soil Resistivity	0.25

Values in Table 9 demonstrate the predominance of IR% indications in the priority response (absolute value of the coefficient), which agrees with the weighting scheme. There is a negative relationship between the Priority Index P and IR%, "OFF" potentials and potential dips, which means the higher these values, the lower the Priority Index, i.e. more severe the indication. There is a positive correlation with soil resistivity, indicating that as resistivity increases, the anomaly decreases in severity.

CONCLUSIONS

A fuzzy logic model is proposed to correlate information from combined CIPS+DCVG coating surveys to the soil resistivity, resulting in an indicator to measure quantitatively the severity (or priority) of anomalies. The model is tested with field survey data, responding satisfactorily to IR% values, pipe-to-soil "OFF" potentials, potential dips and soil resistivity, consolidating information as a single indicator named Priority Index, defined in the interval of 0 to 3, which ranks sets of anomalies in descending order of priority.

The fuzzy logic model provides a coherent approach for severity assessment of multiple sources of information. It is expandable to any number of parameters for which data are available and adaptable to any particular conditions determined by the pipeline operator. The model has a simple implementation and does not rely on specific software. The proposed fuzzy model comes as an additional tool to assist pipeline operators with assessing the condition of their pipelines and prioritizing corrective actions.

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