System for corrosion monitoring in pipeline applying fuzzy logic mathematics

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Abstract. A list of factors influencing corrosion rate on the external side of underground pipeline is determined. Principles of constructing a corrosion monitoring system are described; the system performance algorithm and program are elaborated. A comparative analysis of methods for calculating corrosion rate is undertaken. Fuzzy logic mathematics is applied to reduce calculations while considering a wider range of corrosion factors.

1. Introduction
Corrosion factor is among the causes of early wear of linear pipeline portion. A significant amount of evaluation and monitoring methods for condition of linear pipeline portion are elaborated and implemented to date, including distance techniques. The main issue in modern methods is they focus on one-factor diagnosis, which defines corrosion spread or identification of the real situation of the pipeline wall.

The internal factors of corrosion are determined by metallurgy and metal condition, i.e. they derive from mechanical and thermal metal working. Mechanical working is implemented with cutters, millers, abrasive wheels, etc. This leads to roughness of metal surface, which increases moisture retention and corrosion as a result. Thermal working influences the structure, the phase composition, concentration of alloying elements in a crystal grain. Additionally, compression and tension stress may be applied to surface layers, formed as a result of thermal working.

The external factors of corrosion are determined by the structure and temperature of corrosion environment, velocity of substance transition relative to the metal surface, etc. These factors are capable to influence significantly the corrosion rate, the pattern and even the mechanism.

It should be noted that this approach provides with a possibility of controlling pipeline walls condition and determining duration of repair, but projecting corrosion and explanations of its reasons are problematic to perform.

Meanwhile, there is a strong base of pipeline condition diagnostic tools and methods for evaluating various factors influencing the intensity of the corrosion process. Under these circumstances, it is essential to establish a system of multivariate analysis of these factors, long-term projection of corrosion destruction depth and calculation of linear pipeline remaining life on the criterion of resistance to corrosion.

Such efforts are being made, but they consist of receiving a variety of information into a single database and providing users with a possibility to make a decision on pipeline current condition based on analysis of a large amount of measured factors and accumulated history of their modifications. Processing a large amount of mixed data under a single mathematical model presents significant challenges, unless non-traditional mathematical methods are applied. The issue of applying such
methods for solving problems of this kind comes up nowadays, considering increasing complexity of technical systems and demands for their performance quality under the circumstances of instability, limitations and inaccuracy of source data.

In this regard, it is relevant to apply fuzzy logic mathematics, which appear one of the most rapidly developing and promising avenue in the field of information processing, control and decision-making. In this paper, fuzzy logic methods are applied for the estimation corrosion rates on the external side of underground pipeline.

According to the reference mathematical model, projected potential metal corrosion rate $V_{pp}$ characterizes the depth increase of the external pipeline wall defect at a given moment as a function of corrosion factors activity $K_i$ and allows the defect development on any point of studied wall section. Generally, $V_{pp}$ value is defined:

$$V_{pp} = \sum_{i=1}^{n} K_i,$$

where $n$ is a number of $K_i$ coefficients, taken to calculate the projected potential corrosion rate.

Meanwhile, $K_i$ defines the depth increase of the corrosion defect in time:

$$K_i = f(P_i, t),$$

where $P_i$ [mm] is the defect depth depending on corrosion factor influence; $t$ [years] refers to time.

2. Results and discussion

In this paper, it is offered to undertake calculations according to the model, which includes a fuzzy inference system. Evaluation and application of the system consists of a number of steps. Carrying out steps is performed by means of a fuzzy logic framework [1-6].

Input information of the fuzzy inference system presents somehow measured input variables, which refer to real variables defining condition of linear pipeline portion and nearby soil. Output information of the fuzzy inference system presents an output variable, which in this case is the projected potential corrosion rate.

The following factors serve as input variables: pipeline useful life ($T$, years); pipeline walls stress ($\sigma$, MPa); anaerobic soil rate; specific resistance of soil ($\rho$, $\Omega$·m); steel mark; ionic force of telluric moisture ($\mu$); oxidation-reduction potential of soil, redox-potential ($E$, V); average density of cathode current ($I$, A/m²); soil pH; soil moisture ($W$, %); pipeline wall temperature ($t$, °C).

A list of introduced term sets is provided below.

- $T_1 = \{"short";"long"\}$ is a term set of the 1st linguistic variable “Pipeline useful life”.
- $T_2 = \{"low";"average";"increased";"high"\}$ is a term set of the 2nd linguistic variable “Pipeline walls stress”.
- $T_3 = \{"anaerobic";"aerobic"\}$ is a term set of the 3rd linguistic variable “Anaerobic soil rate”.
- $T_4 = \{"low";"average";"high"\}$ is a term set of the 4th linguistic variable “Specific resistance of soil”.
- $T_5 = \{"non-corrosion-resistant";"corrosion-resistant";"highly-corrosion-resistant"\}$ is a term set of the 5th linguistic variable “Steel mark”.
- $T_6 = \{"low";"average";"high"\}$ is a term set of the 6th linguistic variable “Ionic force of telluric moisture”.
- $T_7 = \{"extremely low";"low";"average";"high"\}$ is a term set of the 7th linguistic variable “Oxidation-reduction potential of soil, redox-potential”.
- $T_8 = \{"low";"average";"high"\}$ is a term set of the 8th linguistic variable “Average density of cathode current”.
- $T_9 = \{"acid";"weakly acid";"neutral";"weakly alkaline";"alkaline"\}$ is a term set of the 9th linguistic variable “Soil pH”.
- $T_{10} = \{"dry";"wet";"highly wet"\}$ is a term set of the 10th linguistic variable “Soil moisture”.


• $T_{11} = \{"low"; "average"; "high"\}$ is a term set of the 11th linguistic variable “Pipeline wall temperature”.
• $T_{12} = \{"low"; "limited"; "average"; "increased"; "high"\}$ is a term set of the 12th linguistic variable “Projected potential corrosion rate”.

Examples of membership functions of input variables 2 and 4 are presented in figure 1.

The projected potential corrosion rate ($V_{pp}$) serves as an output variable. Later on, it is to be the base for further estimation of pipeline remaining life on the criterion of corrosion resistance and decision-making on exploitation and duration of repair.

Mamdani algorithm [7] is applied for calculations, since it is the simplest in terms of parameters and fuzzy inference steps and appropriate for describing the common case of monitoring a linear pipeline portion.

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The functional diagram of the fuzzy inference system is presented in figure 2.

The main steps of fuzzy inference are: forming a rule base of the fuzzy inference system; fuzzificating input variables; aggregating sub-conditions in fuzzy production rules; activating sub-decisions in fuzzy production rules; accumulating decisions of fuzzy production rules; defuzzificating output variables.

Thus, initially known values of all input variables, i.e. the input set, are defined as:

$$K' = \{k_1, k_2, \ldots, k_{11}\}, \quad k_i \in X_i,$$

where $X_i$ is a range of definition of linguistic variable $K_i$. 
Meanwhile, $A_i$ is a fuzzy set within $X$, and its membership function $\mu(x)$, i.e. $A_i = \{k_i; \mu(x)\}$. $K_i$ value serves as an argument of $\mu(x)$, thereby numerical value $b_i = \mu(k_i)$ is defined, which represents a result of fuzzificating sub-condition «$K_i$ is $A_i$».

If there are a few sub-conditions, at the aggregation step a truth degree of a complex statement is determined on the base of the known sub-conditions truth degree:

$$\mu_{N \cdot M}(x) = \mu_N(x) \cup \mu_M(x),$$

where $N, M$ are fuzzy statements, which are sub-conditions of one rule.

At the activation step, a truth degree of a sub-decision «$Y$ is $B$» of each rule is determined as a truth degree of a corresponding condition, determined at the aggregation step.

Thus, truth degree of each sub-decision, included in the fuzzy inference system rule base, are known before the accumulation step. Accumulating is implemented as union of sets $C_1, C_2, \ldots, C_q$, where $q$ refers to a number of sub-decisions in a rule base:

$$\mu(V_{\text{supp}}) = C_1 \cup C_2 \cup \ldots \cup C_q.$$

The fuzzy inference algorithm developed by Mamdani involves application of center of gravity method during fuzzification:

$$B' = \frac{\max \int_{-\infty}^{\infty} V_{\text{supp}} \mu(V_{\text{supp}}) dx}{\max \int_{-\infty}^{\infty} \mu(V_{\text{supp}}) dx},$$

where $\mu(V_{\text{pp}})$ is a membership function of $V_{\text{pp}}$.

The inference system rule base, presented in figure 3, is used for a formal representation of empirical knowledge and expert knowledge as well. In addition, it may be changed, refined, and adapted to a particular case of pipeline laying.

Figure 3. Rule base of fuzzy inference system
The technical system structure is offered for solving monitoring tasks and projecting corrosion rate. The system functions as follows:

- obtaining source data for calculations;
- projecting corrosion rate by applying fuzzy logic mathematics, prompt alarming about corrosion activation;
- archiving and storing data obtained for further analysis;
- data exchange with other systems.

The structure of the system elaborated is presented in figure 4.

The system includes a microprocessor, RAM and EPROM modules, a display module, an interface module, formed and an adjusted knowledge base and fuzzy logic modules: fuzzificator, a reasoning mechanism (fuzzy inference module), defuzzificator.

![Figure 4. Structure of the system implementing projecting corrosion rate](image)

An application program for calculations was developed in Borland C++ Builder environment. It is targeted to perform mathematical calculations accordingly to the method elaborated.

A fragment of the code, which performs fuzzification of pipeline temperature values obtained, is presented below:

```c++
if (Temp<=-10) TempL=1;
if (Temp<0 && Temp>-10) TempL=-0.1*Temp;
if (Temp>-5 && Temp<=5) TempM=0.1*Temp+0.5;
if (Temp>5 && Temp<20) TempM=Temp/5;
if (Temp>15 && Temp<=25) TempH=(1/15)*Temp+4/3;
if (Temp>25) TempH=1;
```

A fragment of the code, which performs calculation of the membership function of potentially projected corrosion rate accordingly to the rule base, is presented below:

```c++
if (TempL) Vcorr[3][1]=TempL;
if (TempM && HumM)
    if (TempL>HumM) Vcorr[3][4]=HumM; else Vcorr[3][4]=TempL;
if (TempH && HumM)
    if (TempH>HumM) Vcorr[3][5]=HumM; else Vcorr[3][5]=TempH;
```

A fragment of the code, which performs accumulating decisions:

```c++
VcorrL=0;
for (c=1;c<=35;c++)
    if (Vcorr[c][1]>VcorrL) VcorrL=Vcorr[c][1];
```
A fragment of the code, which performs defuzzification of the potentially projected corrosion rate value:
\[
V = \frac{0.1 \times V_{corrL} + 0.3 \times V_{corrML} + 0.4 \times V_{corrM} + 0.5 \times V_{corrMH} + 0.6 \times V_{corrMH} + 0.8 \times V_{corrH} + 0.9 \times V_{corrH}}{V_{corrL} + V_{corrML} + 2 \times V_{corrM} + V_{corrMH} + 2 \times V_{corrH}};
\]

A fragment of the code, which performs calculation of pipeline remaining life on the base of the potentially projected corrosion rate value obtained:
\[
T = 0.3 \times \frac{P}{V};
\]

After all calculations are undertaken, the program transmits data obtained on potentially projected corrosion rate and pipeline remaining life to the SCADA-system.

3. Conclusion

Consequently, a list of factors, which influence corrosion rate on external side of underground pipeline, but are not taken into account in known methods, is determined on the base of normative-technical and scientific literature analysis.

A method is developed for calculating potentially projected corrosion rate and pipeline remaining life by the criterion of corrosion resistance. The method allows undertaking calculations considering a wider range of corrosion factors applying fuzzy logic mathematics, which significantly reduces calculations.

The principles of constructing the monitoring system, which is capable of obtaining information on extra corrosion factors, processing it applying fuzzy logic mathematics and projecting a clarified data on pipeline portion corrosion rate, are established.

An algorithm and a program are elaborated for undertaking calculations on potentially projected corrosion rate and pipeline remaining life by the criterion of corrosion resistance.

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