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A fuzzy-based method is proposed to evaluate soil corrosivity from soil properties such as soil resistivity, pH, redox potential, sulfide content and soil type. The fuzzy-based method considers three levels of soil corrosivity, non-corrosive, moderately corrosive and corrosive. This is in contrast to the commonly used 10-point scoring (10-P) method, which has only two classes, corrosive and non-corrosive. Membership functions for each of the soil properties are used to quantify their affinity to the level of soil corrosivity. These membership values form an evaluation matrix from which a weighted vector is developed using pair-wise soil property comparisons. The final classification is determined from the cross product of the weighted vector and the evaluation matrix. Two case studies are examined to validate the application of the proposed fuzzy-based method to predict soil corrosivity and the results are compared to the 10-P method. Both case studies showed that the fuzzy-based method out performed the 10-P method.

Key Words: Corrosion, 10-P method, soil corrosivity, fuzzy-based method, water mains.

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Introduction

Several factors may contribute directly or indirectly to the structural failure of metallic water mains, the most important of which is corrosion. Factors such as casting technology and manufacturing defects contribute to the structural resiliency of the pipe, while specific local and environmental conditions may act to exacerbate or alleviate externally induced stresses.

Water utilities use many criteria to assess the structural condition of pipes, of which the principal are breakage frequency or the growth of corrosion pit depth. In cast iron pipes, corrosion generally takes place in the form of "graphitic corrosion," in which iron leaches out of the material leaving behind the graphite matrix. Hence, a corrosion pit develops but remaining carbon remains intact, therefore reducing the tensile strength of the pipe (Rajani *et al*., 2000). Ductile iron pipe corrodes in the form of distinct "through hole" corrosion pits.

The identification of potentially corrosive environments is therefore very important. If done prior to pipe installation water utilities can save significant future costs and avoid failures by installing externally coated pipes or providing cathodic protection. In an existing water distribution network identifying corrosive environment can save resources by concentrating attention on the sections that are at higher risk (DIPRA, 2000; ANSI/AWWA C105/A21.5–99, 1999; Seica *et al*., 2000; Doyle *et al*., 2003). Corrosion resisting measures are required in most soils with low soil resistivities, the presence of anaerobic bacteria, differences in soil composition, and differential aeration around the pipe. Dissimilar metals and external stray direct currents may also require additional protection against corrosion.

Several evaluation processes have been used to predict conditions corrosive to underground piping. The 10-point scoring (10-P) method was introduced by CIPRA (Cast Iron Pipe Research Association, predecessor to current organization, DIPRA, Ductile Iron Pipe

Association based in Alabama, United States) in 1964 for cast iron pipes and scores currently used for ductile iron pipes are detailed in ANSI/AWWA C105/A21.5–99 (1999). It is perhaps the method most used for cast and ductile iron pipes to determine soil corrosivity. DIPRA (2000) reported that the method has been used in to determine soil corrosivity in more than 100 million feet of pipe installations in North America.

The 10-P method is based on five soil properties; resistivity, pH, redox potential, sulfides and moisture content. A summary of the method is given in Table 1. For a given soil sample, each property is evaluated through this table for its contribution towards the corrosivity of soil. The scores of all five contributing properties are summed up for a given soil sample, and if the total is more than 10, the soil is considered corrosive to ductile/cast iron water mains, requiring corrosion protection measures. This method provides a guideline to determine corrosion due to soil and is only recommended for usage by qualified engineers (ANSI/AWWA C105/A21.5–99, 1999; DIPRA, 2000). In this evaluation process the soil is either classified as corrosive or non-corrosive. The major drawbacks of the 10-P method are:

1. This method does not provide information on the intensity of corrosivity. There are only two possible outcomes to indicate soil corrosivity, e.g., if the score ≥ 10, the soil is classified as corrosive, meanwhile if it is slightly less than 10, say, 9.5, the soil is rated non-corrosive;
2. The 10-P is essentially a weighted-average method, in which the weights are implicit in the specific range of scores assigned for each factor;
3. The drainage characteristics of soils is classified in three categories, without any specific indication of soil type; and
4. The point scores for soil pH in the range of 4 to 8.5 are assigned zero although the pH in this range may also promote corrosion (Gedge, 1993).

Metalogic (1998) also proposed a scoring method encompassing 12 factors for evaluating soil corrosivity. These include type of soil, soil resistivity, water content, pH, buffering capacity, sulfide, chloride and sulfate concentrations, as well as the presence of groundwater, horizontal and vertical soil homogeneities, and electrochemical potential. The intensity scale used for rating the soil is different from the 10-P method. In this method, the soils are divided into 4 categories. Cumulative index values that are less than -10, represent a highly corrosive environment, whereas positive values (> 0) represent virtually non-corrosive conditions. The remaining two classes – slightly corrosive and corrosive lie in the middle as given in Table 2.

The major drawbacks of this method are:

1. As in the 10-P method, this is also a prescriptive weighted average method (with weights implicit in the various score ranges);
2. It is costly and often impractical to collect all the data required for this method;
3. Similar to the 10-P method, the scores for soil pH in the range of 5.5 to 9.0 are assigned zero, contrary to the opinion of some researchers, e.g., Gedge (1993).

A Fuzzy-Based Method for the Evaluation of Soil Corrosivity

Fuzzy logic provides a language with syntax and semantics to translate qualitative knowledge into numerical reasoning. In many engineering problems, the information about the probabilities of various risk items is vaguely known or assessed. The term *computing with words* has been introduced by Zadeh (1996) to explain the notion of reasoning linguistically rather than with numerical quantities. Such reasoning has a central importance for many emerging technologies related to engineering and applied sciences.

When evaluating complex systems, decision-makers, engineers, managers, regulators and other stake-holders often view and perceive quantities in terms of linguistic variables like *very* *high*, *high*, *very low*, *low* etc. The fuzzy set theory is able to deal effectively with these types of uncertain (encompassing vagueness), and linguistic variables can be used to approximate reasoning and subsequently manipulated to propagate the uncertainties throughout the decision process.

Fuzzy techniques are a generalized form of interval analysis, which address uncertain and/or imprecise information. Zadeh (1965) introduced this concept, in which fuzzy numbers are assigned to variables to represent uncertainties. A fuzzy number describes the relationship between an uncertain quantity x and a membership function $\mu(x)$, where $\mu(x)$, ranges between 0 and 1, which ranges between 0 and 1. A fuzzy set is an extension of the traditional set theory (in which x is either a member of set A or not) in that an x can be a member of set A with $\mu(x) = 1$, or not a member with $\mu(x) = 0$. Fuzzy-based methods help in addressing deficiencies inherent in binary logic and are useful in propagating uncertainties through models. The fuzzy-based method provides information on the intensity of scale and are found very helpful in expressing perception, e.g., if a person has a height of 6' (though it is crisp), he might have memberships to *tall*, *medium* and *short* people fuzzy sets as 1, 0.7 and 0.2, respectively. It does not mean that information about his height is "uncertain or vague". Fuzzy sets can equally handle cases when information is vague, i.e. a person is *moderately* tall. In our context, for example, a score of 9.5 based on the 10-P method is rated non-corrosive, but fuzzy sets assign certain membership to its corrosivity potential. So it might be 0.8 corrosive and 0.2 non-corrosive (depending on predefined qualitative scales of corrosivity).

Any shape of a fuzzy number is possible, but the selected shape should be justified by available information. In recent years, fuzzy arithmetic has increasingly been applied to civil and environmental engineering problems. Dou *et al*. (1995), Bardossy *et al*. (1995), Guyonnet *et al*. (2000), Khan *et al*. (2002) and Sadiq *et al*. (2003) are a few recent examples.

Determination of membership functions

In the proposed method, five soil properties are used, including soil resistivity, pH, redox potential, sulfide content and soil type based on percent fines. The first four soil properties are the same as those of the 10-P method, while the last is a more refined surrogate measure of the drainage capacity of the soil. The score scales in the 10-P method lend themselves very well to establish fuzzy rule sets and these were slightly adjusted to maintain function symmetry. Therefore, we based our derivations on the 10-P method and amended them wherever additional information was available. For example, information for pH provided by Gedge (1993), and information for sulfides as described in ASTM (1992) was used. The fuzzy sets for soil type are based on percent fines (different criterion to that in the 10-P method for soil drainage). How each soil property affects the corrosion of iron pipes is detailed in Appendix A of ANSI/AWWA C105/A21.5–99 (1999). In addition, "k_i" factors were introduced as exponents to the triangular and/or trapezoidal shapes representing fuzzy sets in order to control the curvature of their left or right limbs. In this paper, the k_i factors for five soil properties are assigned based on authors' experience and judgement.

Membership functions are defined for three qualitative states, namely, non-corrosive (NC), moderately corrosive (MC) and corrosive (C). The selection of granularity (number of partitions over the universe of discourse of a particular fuzzy set) is an important issue in fuzzy-based modeling. In this paper, three qualitative states of corrosivity are proposed for its simplification and practicality. Corrosivity of pipes is typically measured in terms of pitting rate (mils/year or mm/year) but this rate can vary throughout the life of pipe. If corrosion is active, the instantaneous rate is very high initially and later attenuates as the oxidized by-products protect the pipe. Field measurements of pitting rates are usually not available because pipes are not exhumed and examined in their early lives. Therefore reported maximum pit depths of ageing pipes estimate average pitting rates rather than maximum. Consequently, non-corrosive, moderately corrosive and corrosive states can vary throughout the life of the pipe and relative states need to be established at different life stages of the pipe (De-Rosa and Parkinson, 1986). Breakage rate (number of breaks/year/km) of pipe can be used as a surrogate measure for growth rate of corrosion pits. Data collected for case studies consisted of pipes having ages ranging from 20 to 100 years and therefore the pitting (lower value) and breakage (higher value) rates reflect are terminal values.

Soil Resistivity (ρ)

Moisture content and the concentration of different ions and their mobilities influence the electrical resistivity of the soil. Soil solutions of different concentrations are produced by the action of subsurface water on chemical minerals. In a corrosion cell, electric current flows to the cathode through the soil. Soil resistivity influences the current in corrosion cells, but only where the distance between the anode and the cathode is so large that the drop in the potential in the cell has some significance. The magnitude of the current is inversely proportional to the resistivity of the soil. Low soil resistivity (< 1,500 Ω-cm) will result in higher corrosion probability, while high resistivity (> 3,000 Ω-cm) results in lower corrosion probability.

Three fuzzy numbers representing – non-corrosive, moderately corrosive and corrosive conditions in soil are defined in equations 1 through 3 to express the soil resistivity. In the following equations x is used as a dummy variable representing the argument of the membership functions.

$$\mu_{\rho-C}(x) = \begin{cases} [(2000-x)/200]^{k_1} & ; \quad 1800 < x < 2000 \\ 0 & ; \quad 2000 \le x \\ 1 & ; \quad 1800 \ge x \end{cases} \tag{1}$$

$$\mu_{\rho-MC}(x) = 1 - \mu_{\rho-NC}(x) - \mu_{\rho-C}(x) \tag{2}$$

$$\mu_{\rho-NC}(x) = \begin{cases} [(x-2500)/300]^{k_1} & ; \quad 2500 < x < 2800 \\ 0 & ; \quad 2500 \ge x \\ 1 & ; \quad 2800 \le x \end{cases} \tag{3}$$

where $\mu_{\rho\text{-}C}(x)$ is the membership value of x in the corrosive resistivity set, $\mu_{\rho\text{-}MC}(x)$ is the membership value of x in the moderately-corrosive resistivity set, and $\mu_{\rho\text{-}NC}(x)$ is the membership value of x in the non-corrosive resistivity set, x in the above equations is expressed in Ω-cm. The membership values range between 0 and 1. The memberships to fuzzy sets of corrosive resistivity and non-corrosive are assigned heuristically using information from 10-P method.

The value of factor k_1 should be selected based on observations and/or expert opinion. In the literature, values of k_1 vary approximately from 1 to 4 (e.g., Lu *et al*., 1999). Figure 1 illustrates the membership function for soil resistivity when $k_1 = 1.2$, e.g., at $\mu_{\rho\text{-}C}(x) = 0.5$, the x is approximately 1,890 Ω-cm. At this value of x, the $\mu_{\rho\text{-}MC}(x)$ is also equal to 0.5 (using equation 2). Similarly, $\mu_{\rho\text{-}NC}(x)$ is 0.5 at x = 2,670 Ω-cm (using equation 3). The $\mu_{\rho\text{-}MC}(x)$ is also 0.5 (using equation 3) for this value of x. The values of soil resistivity at $\mu(x) = 0.5$ for various corrosivity levels are summarized in Table 3.

Soil pH (p)

The pH value of the soil is generally determined by the contents of carbonic acid, various minerals (and/or their leaching), organic and inorganic acids (produced by microbial activities) and by disposal of industrial wastes and/or acid rain. Highly acidic soils (pH < 4, such as peat and soils beneath heavy accumulations of acidic vegetable materials) are rare, the pH usually ranges between 5 to 8, resulting in moderate corrosion potential.

Equations 4 through 6 define the membership values of three fuzzy numbers. These values define the memberships in sets of soil pH, representing corrosive, moderately corrosive, and non-corrosive conditions.

$$\mu_{p-C}(x) = \begin{cases} [(5-x)/2]^{k_2} & ; \quad 3 < x < 5 \\ 0 & ; \quad 5 \le x \\ 1 & ; \quad 3 \ge x \end{cases} \tag{4}$$

$$\mu_{p-MC}(x) = 1 - \mu_{p-NC}(x) - \mu_{p-C}(x) \tag{5}$$

$$\mu_{p-NC}(x) = \begin{cases} [(x-8)/2]^{k_2} & ; \quad 8 < x < 10 \\ 0 & ; \quad 8 \ge x \\ 1 & ; \quad 10 \le x \end{cases} \tag{6}$$

where $\mu_{p-C}(x)$ is the membership value of x in the corrosive set, $\mu_{p-MC}(x)$ is the membership value of x in the moderately-corrosive set, and $\mu_{p-NC}(x)$ is the membership value of x in the non-corrosive set, x in the above equations represents pH which is unitless. Figure 2 illustrates the membership function for $k_2 = 1.2$. The values of pH for three corrosivity levels at $\mu(x) = 0.5$ are given in Table 3. The memberships of corrosive and non-corrosive fuzzy sets of pH are derived using data from Gedge (1993).

Redox Potential (Rp)

The oxygen concentration of the soil moisture generally determines redox potential. Higher oxygen content implies higher redox potential. A corrosion (galvanic) cell may develop when the concentration of oxygen varies along the surface of a buried metallic structure. Differences in redox potential can thus point to corrosion potential (Metalogic, 1998).

Equations 7 through 9 define the membership values of three fuzzy numbers. These values define the memberships in sets of soil redox potential, representing corrosive, moderately corrosive, and non-corrosive conditions.

$$\mu_{Rp-C}(x) = \begin{cases} [(25-x)/45]^{k_3} & ; \quad -20 < x < 25 \\ 0 & ; \quad 25 \le x \\ 1 & ; \quad -20 \ge x \end{cases} \tag{7}$$

$$\mu_{Rp-MC}(x) = 1 - \mu_{Rp-NC}(x) - \mu_{Rp-C}(x) \tag{8}$$

$$\mu_{p-NC}(x) = \begin{cases} [(x-50)/50]^{k_3} & ; \quad 50 < x < 100 \\ 0 & ; \quad 50 \ge x \\ 1 & ; \quad 100 \le x \end{cases} \tag{9}$$

where $\mu_{Rp\text{-}C}(x)$ is the membership value of x (redox potential) in the corrosive set, $\mu_{Rp\text{-}MC}(x)$ is the membership value of x in the moderately-corrosive set, and $\mu_{Rp\text{-}NC}(x)$ is the membership value of x in the non-corrosive set, x in the above equations is in mV. Figure 3 illustrates the membership function for $k_3 = 1.2$. The values of redox potential for three corrosivity levels at $\mu(x) = 0.5$ are given in Table 3.

Sulfides (s)

Microbiological corrosion might be an important component leading to cast iron pipe deterioration. Sulfate reducing bacteria metabolize sulfates into sulfides, hence an easy way to test the soil for the presence of microbial activity is to analyze soil samples for sulfide content. Generally sulfides are reported as positive, trace and negative.

Equations 10 through 12 define the membership values of three fuzzy numbers. These values define the memberships in sets of sulfide concentration in the soil, representing corrosive, moderately corrosive, and non-corrosive conditions.

$$\mu_{s-C}(x) = \begin{cases} [x]^{k_4} & ; \quad 0 < x < 1 \\ 0 & ; \quad 0 \geq x \\ 1 & ; \quad 1 \leq x \end{cases} \tag{10}$$

$$\mu_{s-MC}(x) = 1 - \mu_{s-NC}(x) - \mu_{s-C}(x) \tag{11}$$

$$\mu_{s-NC}(x) = \begin{cases} [0-x]^{k_4} & ; \quad -1 < x < 0 \\ 0 & ; \quad 0 \leq x \\ 1 & ; \quad -1 \geq x \end{cases} \tag{12}$$

where $\mu_{s-C}(x)$ is the membership value of x (sulfide content, expressed as log of concentration) in the corrosive set, μ_{s-MC} is the membership value of x in the moderately-corrosive set, and $\mu_{s-NC}(x)$ is the membership value of x in the non-corrosive set; x in the above equations is in ppm. Figure 4 illustrates the membership function for k_4 = 1.0. The values of sulfide for three corrosivity levels at $\mu(x)$ = 0.5 are given in Table 3. Selection of k_4 =1.0 is made because generally sulfide data are reported as positive (significant concentration), negative (negligible) or trace (low concentration) (ASTM, 1992). The membership function can also be established based on concentration of sulfide ions based on availability of more reliable information.

Soil type (F)

It is proposed that soil type be used as surrogate measure for drainage characteristics. Soil type can be broadly inferred from percent fines content. Table 4 summarizes various soil types and the corresponding percent fines or clay (particle size < 0.074 μm) measured as percent weight. Higher values of percent fines represent greater moisture retaining capacity, which often causes poor drainage, leading to higher soil corrosivity.

Equations 13 through 15 define the membership values of three fuzzy numbers. These values define the memberships in fuzzy sets of soil type, representing corrosive, moderately corrosive, and non-corrosive conditions.

$$\mu_{F-C}(x)=\begin{cases}[(x-30)/15]^{k_5} & ; \quad 30 < x < 45\\ 0 & ; \quad 30 \geq x\\ 1 & ; \quad 45 \leq x\end{cases} \qquad (13)$$

$$\mu_{F-MC}(x)=1-\mu_{F-NC}(x)-\mu_{F-C}(x) \qquad (14)$$

$$\mu_{F-NC}(x)=\begin{cases}[(30-x)/10]^{k5} & ; \quad 20 < x < 30\\ 0 & ; \quad 30 \leq x\\ 1 & ; \quad 20 \geq x\end{cases} \qquad (15)$$

where $\mu_{F\text{-}C}(x)$ is the membership value of x (percent fines) in the corrosive set, $\mu_{F\text{-}MC}(x)$ is the membership value of x in the moderately-corrosive set, and $\mu_{F\text{-}NC}(x)$ is the membership value of x in the non-corrosive set; x in the above equations is in percentage (%). Figure 5 illustrates the membership function for k_5 = 1.2. The soil type values based on percent fines for three corrosivity levels at $\mu(x)$ = 0.5 are reported in Table 3.

Weighting scheme

Generally, multi-criteria analysis (MCA) requires information about the relative importance of attributes or criteria. Its relative importance is usually established by a set of preference weights, which can be normalized to a sum of 1. In case of n criteria, a set of weights can be written as

$$W=(w_1, w_2,..., w_n) \quad \text{where} \quad \sum_{j=1}^{n} w_j = 1 \qquad (16)$$

Saaty (1988) proposed an analytic hierarchy process (AHP) to estimate the relative importance of each attribute (in a group) based on pair-wise comparisons. Lu *et al*. (1999), Sadiq *et al*. (2003), and Khan *et al*. (2002) used a simple technique in MCA for calculating the weights for different attributes. The relative importance of different factors can be assigned using intensity of importance as given in Table 5. An importance matrix, J, can be established where each element, j_{mn}, in the upper triangular matrix expresses the importance intensity of a criterion (or property) *m* with respect to another criterion *n*. For example, in the importance matrix, *J*, below, soil resistivity has been assigned an importance intensity 3 times greater than pH. Each element in the lower triangle of the matrix is the reciprocal of upper triangle, i.e., $j_{nm} = 1/j_{mn}$. The value of each element, j_{mn}, in *J* above should be assigned based on expert opinion on how the different soil properties influence corrosion of cast iron water mains under the specific circumstances at hand. In this study, an internet-based survey was conducted where over 20 corrosion specialists were asked a variety of questions on how different soil properties influence the corrosion of cast and ductile iron water mains (Najjaran *et al*., 2003). The importance matrix, *J*, largely based on the survey results is:

$$J = \begin{array}{c} \begin{matrix} \rho & p & Rp & s & F \end{matrix} \\ \begin{bmatrix} 1 & 3 & 4 & 6 & 8 \\ 0.33 & 1 & 1.5 & 2 & 4 \\ 0.25 & 0.67 & 1 & 2 & 2 \\ 0.16 & 0.5 & 0.5 & 1 & 2 \\ 0.13 & 0.25 & 0.5 & 0.5 & 1 \end{bmatrix} \end{array} \begin{matrix} \rho \\ p \\ Rp \\ s \\ F \end{matrix} \qquad (17)$$

Members j_{mn} can be modified as required, if better information becomes available. A matrix *I* can be determined by normalizing matrix *J* column wise. The weighted vector *I'* can be derived by taking the summation of the elements of each row of normalized matrix *I* (Lu *et al*., 1999).

$$I = \begin{bmatrix} 0.533 & 0.553 & 0.533 & 0.522 & 0.471 \\ 0.178 & 0.185 & 0.200 & 0.174 & 0.235 \\ 0.133 & 0.123 & 0.133 & 0.174 & 0.118 \\ 0.089 & 0.092 & 0.067 & 0.087 & 0.118 \\ 0.067 & 0.046 & 0.067 & 0.087 & 0.059 \end{bmatrix} \Rightarrow I' = \begin{bmatrix} 2.61 \\ 0.97 \\ 0.68 \\ 0.45 \\ 0.28 \end{bmatrix} \qquad (18)$$

The final weighted vector *W* can be obtained by normalizing and taking the transpose

$$W = [\, w_R \quad w_p \quad w_{Rp} \quad w_S \quad w_F \,] = [0.523 \quad 0.194 \quad 0.136 \quad 0.090 \quad 0.056] \qquad (19)$$

The above weighted vector W indicates that based on the pair-wise importance j_{nm} selected above, soil resistivity has the most influence on soil corrosivity while soil type has the least.

Fuzzy evaluation matrix

Equations 1 through 15, established membership values $\mu(x)$ for three levels of soil corrosivity - corrosive, moderately corrosive, and non-corrosive - for each soil property. These membership values are used to set up an evaluation matrix ***R***, where each row represents membership values that correspond to one of the three levels of corrosivity C, MC, NC for each soil property ρ (resistivity), p (pH), Rp (redox potential), s (sulfide content) and F (soil type defined by percent fines). The weight vector $\boldsymbol{W} = [\, w_R \quad w_p \quad w_{Rp} \quad w_s \quad w_F \,]$ is multiplied by ***R*** to determine fuzzy evaluation matrix ***B***.

$$\boldsymbol{B} = \boldsymbol{W} \times \boldsymbol{R} = [\, w_R \;\, w_p \;\, w_{Rp} \;\, w_s \;\, w_F \,]_{(1,5)} \times \begin{bmatrix} \mu_{R-C} & \mu_{R-MC} & \mu_{R-NC} \\ \mu_{p-C} & \mu_{p-MC} & \mu_{p-NC} \\ \mu_{Rp-C} & \mu_{Rp-MC} & \mu_{Rp-NC} \\ \mu_{s-C} & \mu_{s-MC} & \mu_{s-NC} \\ \mu_{F-C} & \mu_{F-MC} & \mu_{F-NC} \end{bmatrix}_{(5,3)} = [\, b_C \;\, b_{MC} \;\, b_{NC} \,] \qquad (20)$$

A process known as *defuzzification*, which means to calculate the crisp value of fuzzy number, determines the assessment of corrosivity scale. Many different defuzzification techniques are available (Chen and Hwang, 1992; Lee, 1990a, b), but the one selected in equation (21) below is that method from Cheng and Lin (2002). It uses the maximum operator to determine corrosivity classification membership from matrix ***B***. This method provides similar results as by *first of maximum*, *last of maximum*, and *mean of maximum* defuzzification methods, and is also used here for its simplicity.

$$\boldsymbol{K} = max.\ \{b_C, b_{MC}, b_{NC}\} \tag{21}$$

K is thus the overall dominant characteristic of the soil corrosivity level.

Validation of Method

To validate the predictive quality of a soil corrosivity model one has to compare its predictions with observed data. Since there are no corrosivity data per se, two acceptable surrogate measures are used, breakage rate (often expressed as number of breaks/year/km of pipe) and growth rate of corrosion pits. While breakage rate is relatively easy to obtain from the data records of water utilities, the growth rate of a corrosion pit varies with time and can only be reliably determined if the growth of corrosion pits is tracked at different times. Therefore, generally an average value is determined from one snapshot measurement at a very late stage of the water main deterioration. The following sections describe two case studies to validate the proposed method. Case study A uses pipe breakage rates (Bk-R) and Case study B uses average growth rate of corrosion pit (Co-R) with maximum depth, as surrogate (observed) measures for soil corrosivity. Pipes investigated in both case studies were not protected against corrosion (e.g., cathodic protection or external coatings).

Case study A

In city A (located in Canada), pipe breakage rates and age were available at 50 locations, but soil property data were available for 70 locations. The observed average breakage rates ranged from a high of 1.8 breaks/km/yr to a low of zero. In order to validate the fuzzy-based model, this range is divided into three equal sub-ranges or classes; ≥ 1.2, 0.6-1.2, and < 0.6 breaks/km/yr, corresponding to the three levels of soil corrosivity C, MC and NC defined earlier (Table 6). Similarly, in order to validate the 10-P method for comparison, the same range is divided into two classes ≥ 0.9 and < 0.9 breaks/km/yr, corresponding to the two levels of soil corrosivity (corrosive and non-corrosive) defined in the 10-P method (Table 6). The fuzzy-based and 10-P methods were applied.

Table 7 shows how these two methods compare in their ability to predict the level of observed breakage rates. Table 7 shows the percentage of exact predictions of the fuzzy-based method, as well as one-level misses (e.g., predicting NC where the validation data indicate MC) and two-level misses (e.g., predicting NC where the validation data indicate C). In the 10-P method, since there are only two classes (corrosive and non-corrosive) every miss is considered equivalent to a two-level miss. It can be seen that the fuzzy-based method had 70% exact matches compared to 60% for the 10-P method.

Another way to compare success rate is to define an expected loss or penalty function E (L) for missing a prediction. In this way the magnitude (or level) of the miss is considered as well:

$$E(L) = \sum [\text{probability} \times \text{penalty (or consequences)}] \text{ therefore,} \qquad (22)$$

The selected penalty weights for the fuzzed-based and 10-P methods are (2-1-0) and (2-0), respectively. These values are selected to account for the fact a 1-level miss must have a lesser adverse consequence than a 2-level miss. Furthermore, the 10-P method is considered to have a 2-level miss because it does not have an intermediate response level. This may introduce some bias into the comparison of the penalty values of the two methods (the selection of granularity, i.e., the number of partitions in the universe of discourse, is very important in fuzzy-based modeling and a consensus needs to be established among the experts on this issue). Hence, expected misses are:

$E(L)_{(Fuz)} = \{4\% \times 2 + 26\% \times 1 + 70\% \times 0\}/100 = 0.34$ for the fuzzy-based method; and

$E(L)_{(10\text{-}P)} = \{40\% \times 2 + 60\% \times 0\}/100 = 0.80$ for the 10-P method.

The fuzzy-based model is better able to predict soil corrosivity (expressed in average breakage rate) than the 10-P method. Even if the penalty for the 10-P method were considered as only 1-level miss, the expected loss would still higher than that with the fuzzy-based method. In this paper, three granular states are used for simplification and practicality, though higher granular states may improve the results, and further research is required in this direction.

Case study B

The second case study is based on data collected from various North American cities to study the growth of corrosion pits in cast iron pipes. Corrosion pit growth rate (Co-R) is taken as surrogate measure for soil corrosivity. The average corrosion pit depth is divided by the age of pipe to determine the average corrosion growth rate (mm/year). As explained earlier, this estimate is a snapshot of the conditions at the time of sample collection. Similar to Case A, the Co-R data were also categorized in the fuzzy-based method. For the 10-P method, pit growth rates divided into two classes; >0.038 and < 0.038 mm/yr, corresponding to corrosive and non-corrosive classes (Table 6).

A complete data set was available for 45 locations. Table 7 shows that an exact match is obtained for 71% of data analyzed by the fuzzy method, and for 67% of the data analyzed by the 10-P method. The value of the expected loss function is 0.18 for the fuzzy-based method, which is lower than 0.33 obtained for the 10-P method.

Summary and Conclusions

A new method to evaluate soil corrosivity using a fuzzy-based approach was introduced. The method uses properties like soil resistivity, pH, redox potential, sulfide content and soil type. These soil properties are similar to those used by the 10-P scoring method, with the exception that soil type (expressed in percent fines) replaces soil drainage. The fuzzy-based method partitions the response space into three levels, non-corrosive, moderately corrosive and corrosive. This is in contrast to the 10-P method, with two classes, corrosive and non-corrosive. Membership functions were introduced for each of the five indicators, to quantify the affinity of each indicator level to corrosivity (response) level. The membership values were then collated into an evaluation matrix. A weighted vector is created using AHP a well-established method of pair-wise comparisons among all indicators. The cross product of the weighted vector and the evaluation matrix is a vector whose members define the weighted affinities of the specimen at hand to each of the response levels, NC, MC and C. The specimen is then defined (defuzzified) by the member reflecting the highest affinity value.

For validation, the fuzzy-based method and 10-P method were compared for their ability to predict soil corrosivity. Two case studies were examined. In the first case, pipe average breakage rate is taken as a surrogate measure for soil corrosion. In the second case, the average corrosion pitting rate is taken as a surrogate for soil corrosivity. In the first case study, the fuzzy-based method out performed the 10-P method in terms of expected misses.

The proposed fuzzy-based method provides a rational approach, which is flexible and adaptable to specific conditions. Further, it explicitly considers information about the intensity of each prediction through weighted membership functions. The proposed method is very general and can be expanded to any number of indicators for which data are available. It can therefore be used also to test potential candidate indicators to screen out those which provide no additional predictive capabilities. The proposed method also easily lends itself to a simple computer application. It can also be linked to GIS, where soil corrosivity potential on the map will highlight the most vulnerable locations in the water distribution system.

The granularity is an important issue in fuzzy-based modeling. In this paper, three levels of corrosivity were used for its simplification and practicality. A consensus needs to be established among the experts to use more than three granular states though it is a challenging to relate 5 (and more) granulars with breakage rates and corrosion rates (in the absence of data and expert opinions). Further research is required in this direction.

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Table 1.
Soil evaluation for ductile/cast iron pipe using 10-P method (after ANSI/AWWA C105/A21.5–99, 1999; DIPRA, 2000).

Soil	Values and characteristics	Points
Resistivity (Ω-cm)	< 1,500	10
	≥ 1,500 - 1,800	8
	> 1,800 - 2,100	5
	> 2,100 - 2,500	2
	> 2,500 - 3,000	1
	> 3,000	0
pH	0 - 2	5
	2 - 4	3
	4 - 6.5	0
	6.5 - 7.5	0
	7.5 - 8.5	0
	>8.5	3
Redox potential (mV)	> +100	0
	+50 - +100	3.5
	0 - +50	4
	< 0	5
Sulfides	Positive	3.5
	Trace	2
	Negative	0
Moisture	Poor drainage (continually wet)	2
	Fair drainage (generally moist)	1
	Good drainage (generally dry)	0

Table 2.
Corrosivity of soil (after Metalogic, 1998).

Soil Corrosivity	*I = $\sum_{i}^{12} r_i$
Virtually not corrosive	>0
Slightly corrosive	-1 to -4
Corrosive	-5 to -10
Highly corrosive	<-10

**ri* represents the performance indices for 12 contributing factors *i*, (see reference for details)

Table 3.
Values of soil properties at membership function $\mu(x) = 0.5$.

Soil property	Units	$\mu_{j\text{-}NC}(x) = \mu_{j\text{-}MC}(x)$	$\mu_{j\text{-}MC}(x) = \mu_{j\text{-}C}(x)$
Soil resistivity (ρ)	(Ω-cm)	2670	1890
pH (p)	-	9.1	3.9
Redox potential (Rp)	(mV)	78	0
Sulfide (s)	log(ppm)	-0.5	0.5
Soil type defined by percent fines (F)	(%)	24.4	38.4

Table 4.
Soil classification based on percent of fines.

Soil type	% clay (soil particles < 0.002 mm) fines by weight
Granular material (gravel)	15
Sand	22
Silty sand	25
Silt	30
Silty clay	35
Clay	> 40

Table 5.
Linguistic measures of importance (after Saaty, 1988).

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

Table 6.
Comparison of breakage and corrosion growth rates data with predictions made by 10-P and fuzzy-based methods for case studies A and B.

Comparison	Method	Data points	Number of comparison	Corrosive (C)	Moderately corrosive (MC)	Non-corrosive (NC)
Case study A			50			
10-P vs. Bk-R	10-P	70		≥ 10		< 10
	[1]Bk-R	50		≥ 0.9		< 0.9
Fuzzy vs. Bk-R	Fuzzy	70		$\mu_C > \mu_{MC}, \mu_{NC}$	$\mu_{MC} > \mu_C, \mu_{NC}$	$\mu_{NC} > \mu_C, \mu_{MC}$
	Bk-R	50		≥ 1.2	1.2 > Bk-R ≥ 0.6	< 0.6
Case study B			45			
10-P vs. Co-R	10-P	45		≥ 10		< 10
	[2]Co-R	45		≥ 0.038		< 0.038
Fuzzy vs. Co-R	Fuzzy	45		$\mu_C > \mu_{MC}, \mu_{NC}$	$\mu_{MC} > \mu_C, \mu_{NC}$	$\mu_{NC} > \mu_C, \mu_{MC}$
	Co-R	45		≥ 0.050	0.050 > Co-R ≥ 0.025	< 0.025

1: Breakage rate (Bk-R or number of breaks/km/yr);
2: Corrosion pit growth rate (Co-R or mm/yr)

Table 7.
Percentage match in assessment of soil corrosivity using proposed method fuzzy-based and 10-P methods for case studies A and B.

Methods	Fuzzy-based				10-P			
Case study / Surrogate measure	Difference in corrosion levels (%)			Loss function	Difference in corrosion levels (%)			Loss function
	0s†	1s	2s		0s	1s	2s	
A / breakage rate	70	26	4	0.34	60	0	40	0.80
B / corrosion rate	71	22	7	0.36	67	0	33	0.66

† This table should be read as follows: 0 difference means correct prediction, therefore the fuzzy-based method predicted correctly 70% of the sample in case study A, had a one-level (e.g., predicted NC but the true reading was MC) miss in 26% of the sample and a two-level miss (e.g. predicted NC but the true reading was C) in 4% of the sample.

List of Figures

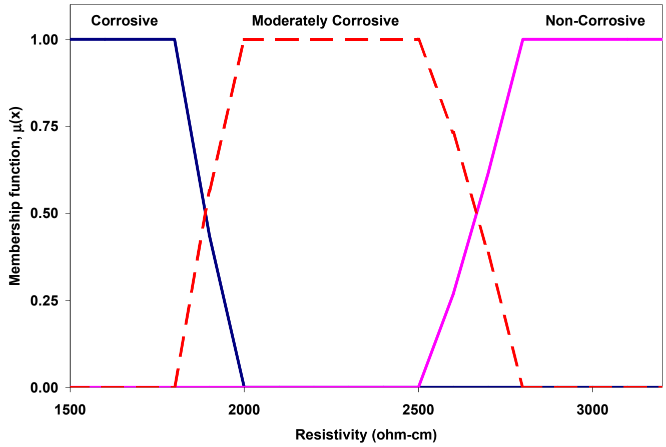
Corrosive
Moderately Corrosive
Non-Corrosive
1.00
0.75
0.50
0.25
0.00
Membership function, μ(x)
1500
2000
2500
3000
Resistivity (ohm-cm)

Figure 1.

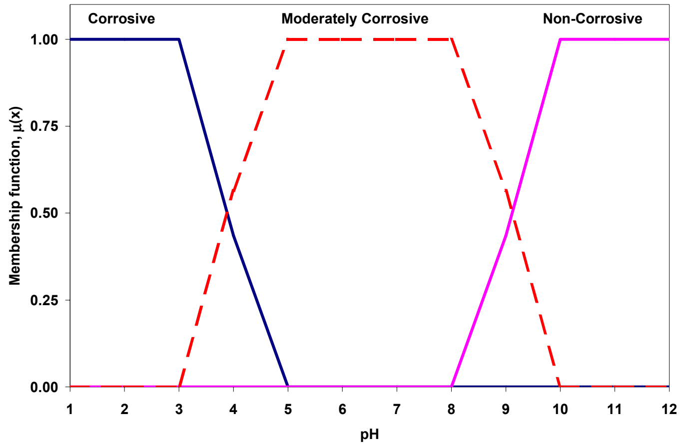
Corrosive
Moderately Corrosive
Non-Corrosive
1.00
0.75
0.50
0.25
0.00
Membership function, μ(x)
1
2
3
4
5
6
7
8
9
10
11
12
pH

Figure 2.

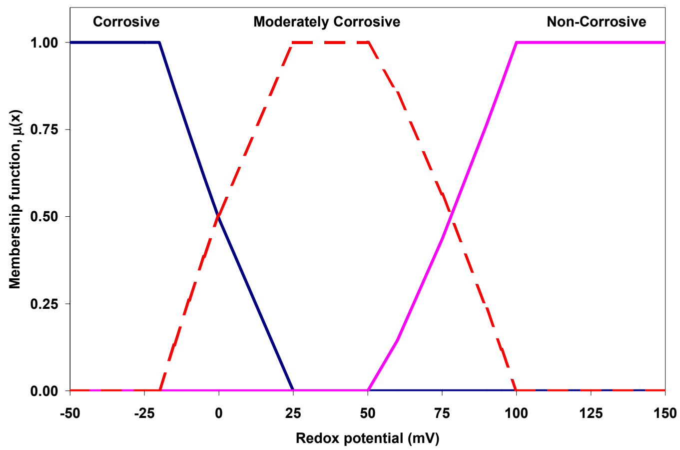
Corrosive
Moderately Corrosive
Non-Corrosive
1.00
0.75
0.50
0.25
0.00
Membership function, µ(x)
-50
-25
0
25
50
75
100
125
150
Redox potential (mV)

Figure 3.

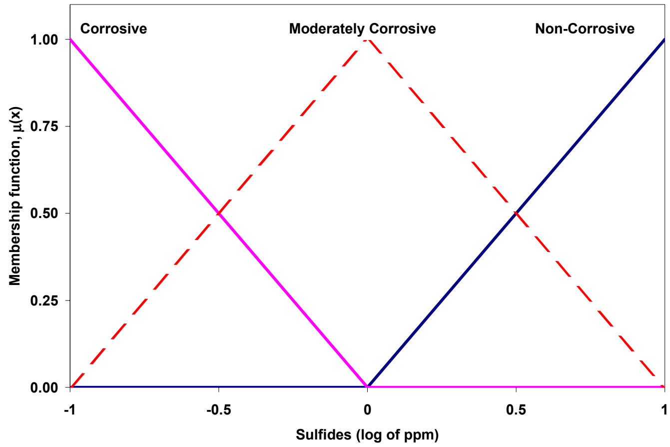
Corrosive
Moderately Corrosive
Non-Corrosive
1.00
0.75
0.50
0.25
0.00
Membership function, μ(x)
-1
-0.5
0
0.5
1
Sulfides (log of ppm)

Figure 4.

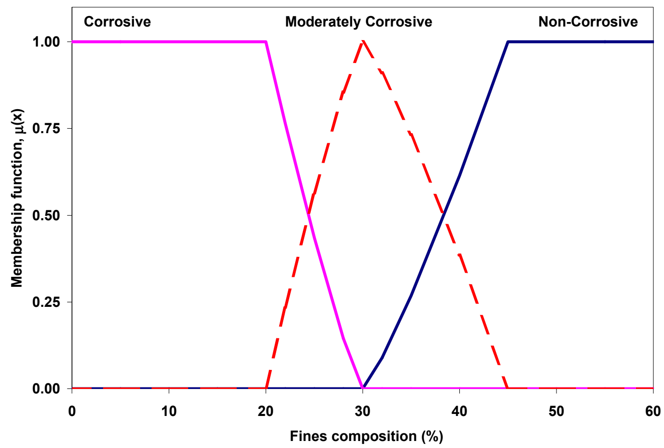
Corrosive
Moderately Corrosive
Non-Corrosive
1.00
0.75
0.50
0.25
0.00
Membership function, μ(x)
0
10
20
30
40
50
60
Fines composition (%)

Figure 5.