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Modeling Pipe Deterioration using Soil Properties –
An Application of Fuzzy Logic Expert System

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Abstract

Several factors may contribute to the structural failure of cast/ductile iron water mains, the most important of which is considered to be corrosion. The ANSI/AWWA C105/A21.5–99 10-point scoring (10-P) method is the most common method used to predict soil corrosivity potential, which is based on soil properties. For a given soil sample, each soil property is evaluated for its contribution towards the corrosivity of soil. The 10-P method uses binary logic to classify the soil, either as corrosive or non-corrosive.

Fuzzy logic extends the binary logic in this context as it recognizes the real world phenomena in which each property has certain degree of membership between 0 and 1. The main objective of the present research is to develop a fuzzy logic expert system capable of establishing a criterion (such as corrosion rate or breakage rate) for predicting the deterioration of cast/ductile iron water mains using soil properties. The proposed expert system includes a fuzzy model consisting of a series of IF-THEN rules to determine soil corrosivity potential (*CoP*) based on soil properties. The fuzzy model contains the data of linguistic variables (database) characterizing various soil properties, and a rule base that constructs relationships among those properties and *CoP*. Subsequently, the expert system uses a linear regression model to link *CoP* to the deterioration rate of metallic pipes. A case study on cast iron pipes is examined to illustrate the application of the proposed expert system.

1. Introduction

Several factors may contribute directly or indirectly to the structural failure of metallic pipes. Factors such as casting and manufacturing defects may have an impact on the structural resilience of the pipe, while specific local and environmental conditions may act to exacerbate stresses. Approximately 700 water-main breaks are reported in North America everyday, which account for repair costs of approximately $1 billion annually (Lary, 2000). It is now widely accepted that most breaks do not only reflect pipe age, but corrosion is found to play a major role in their premature failures (Spickelmire, 2002).

Water utilities use various criteria to assess the structural deterioration of pipes, among which breakage frequency and corrosion pitting rates are the principal ones. Deterioration modeling of water mains is an essential element to guide decision making in pipe rehabilitation or renewal programs. A valid deterioration model must account for current and future pipe conditions. Different mathematical and statistical techniques have been developed to model pipe deterioration. Probabilistic models are widely used in infrastructure deterioration modeling. Among this class of models, significant efforts have been dedicated to Markov-based models and their derivatives. Some researchers have focused on logistic regression-based models, while other used Bayesian-based methods mainly in conjunction with other methods. There is a great deal of literature describing past and ongoing work on decision making for repair/renew/replacement of water mains. Rajani and Kleiner (2001) and Kleiner and Rajani (2001) provided comprehensive reviews of the published work related to physical and statistical models, respectively. In recent years, however, increasing research effort in modeling of infrastructure deterioration has been dedicated to fuzzy based methods (e.g., Sadiq *et al.*, 2004), primarily because available data are often qualitative and field data are either unavailable or uncertain and vague.

Identification of potentially corrosive environments is a precursor in deterioration modeling. If done prior to pipe installation, water utilities can save significant future costs and avoid failures by installing externally coated pipes or providing appropriate mitigation against corrosion. In addition, identification of corrosive environment for existing pipes can save resources by focussing attention on the pipe sections that are at high risk (Seica *et al.*, 2000; Doyle *et al.*, 2003). Corrosion protection measures are usually required in backfills (term synonymously used with soil(s) in this paper) with low resistivity, presence of anaerobic bacteria, differences in soil composition, and differential aeration around the pipe.

Several techniques are currently in use to assess conditions that are corrosive to buried piping. The 10-point scoring (10-P) method was introduced by CIPRA (Cast Iron Pipe Research Association, predecessor of DIPRA, Ductile Iron Pipe Research Association) in 1964 for cast iron pipes, which was subsequently extended to ductile iron pipes (ANSI/AWWA C105/A21.5–99). The 10-P method uses five soil properties - resistivity, pH, redox potential, sulfides, and moisture content. A summary of the method is provided in Table 1. If the sum of the scores of all five contributing properties for a given soil sample exceeds 10, the soil is considered "corrosive" to the pipes, requiring corrosion protection measures usually in the form of polyethylene wraps (DIPRA, 2000; Dechant and Smith, 2004). This method essentially classifies the soil as either "corrosive" or "non-corrosive". The 10-P method cannot provide information on the intensity of corrosivity. For instance, if the score is 10, the soil is classified as "corrosive", however, if it is only slightly less than 10, say 9.5, the soil is rated as non-corrosive whereas in reality the latter may not be significantly different from the former.

This paper presents the application of an expert system to estimate a pipe deterioration rate (based on maximum pit depth and pipe age) using a fuzzy model that relates pipes' external corrosion to surrounding soil properties. An overview of fuzzy modeling is presented in Section 2. The inputs and output of the fuzzy model are discussed for a case study in Section 3. The output of the fuzzy model is a proposed corrosivity criterion named corrosivity potential (*CoP*). The relationship between the *CoP* and deterioration rate is explained in Section 4. Section 5 presents the conclusions.

2. *Fuzzy Rule Base Modeling*

In recent years, fuzzy-based methods have increasingly been applied to civil and environmental engineering problems from evaluation of concrete structures to water quality modeling (e.g., Bardossy *et al.*, 1995; Dou *et al.*, 1995; and Guyonnet *et al.*, 2000). In many engineering problems, the available information is vague and sometimes even measured data (or expert knowledge) is too imprecise to justify the use of numbers. Fuzzy logic provides a language with syntax and semantics to translate qualitative knowledge into numerical reasoning.

Table 1 Scores of soil properties used in the 10-P scoring method

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 (continuously wet)	2
	Fair drainage (generally moist)	1
	Good drainage (generally dry)	0

The evaluation of complex systems is often described vaguely by decision-makers (e.g., water utility managers, regulators, and engineers) that may be translated into linguistic variables - *very high*, *high*, *low*, *very low*, etc. A linguistic variable can be a fuzzy number, but fuzzy numbers can also represent numerical variables without being firmly connected to linguistic terms. A fuzzy number is a normal, convex and bounded fuzzy set in a continuous universe of discourse U. A fuzzy set is a collection of ordered pairs $A=\{x,\mu(x)\}$ that describes the relationship between an uncertain quantity x and a membership function $\mu(x)$, where $\mu(x)\in[0,1]$ (Klir and Yuan, 1995; Lee, 1990a, b).

The fuzzy set theory is an extension of the traditional set theory in which x is either a member of set A with $\mu(x)=1$ or not a member of A with $\mu(x)=0$. Fuzzy logic helps to address the inherent deficiencies of binary logic to account for uncertainties. Fuzzy models formulate the information on an intensity scale. For example, soil with a score of 9.5 in the 10-P method would be rated "non-corrosive", but a fuzzy-based method may classify the soil as 0.8 "corrosive" and 0.2 "non-corrosive" (depending on predefined qualitative scales of *CoP*).

A fuzzy model determines the relationships between the output and inputs of a system using *antecedent* and *consequent* propositions in a set of IF-THEN rules. The model of a multi-input single-input (MISO) system is formulated in a rule base that is composed of a number of IF-THEN rules like the following:

$$R_i:\ \text{IF}\ x_1\ \text{is}\ A_{i1}\ \text{AND}\ x_2\ \text{is}\ A_{i2}\ \text{AND}\ \ldots\ x_j\ \text{is}\ A_{ij}\ \text{THEN}\ y\ \text{is}\ B_i\ ,\quad i=1,\ldots,n \qquad (1)$$

where R_i represents the i^{th} rule, n is the total number of rules, x_j $(j=1,\ldots,r)$ are the input variables, y is the only output variable, A_{ij} are input fuzzy numbers defined in the input space specified by r universes of discourse $U=U_1\times\cdots\times U_r$, and B_i is the output fuzzy number defined in the output universe of discourse V. Thus, every rule is a local fuzzy relationship in $U\times V$ that maps a part of the multidimensional input space U into a certain part of the output space V.

The rule base of a complex system usually contains a number of local rules to describe the behavior of a system for all possible values of the input variables. This property of the fuzzy model is referred to as "completeness". The aggregation of the local rules of Eq. (1) forms a global rule base that is valid over the entire application domain and is given by,

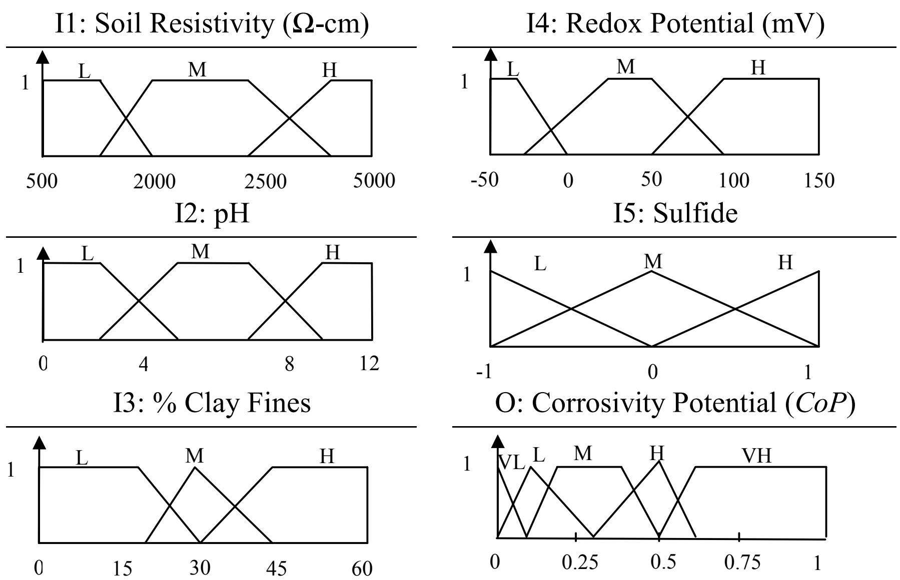
$$R=\bigcup_{i=1}^{n}R_i=\ R_1\ \text{ALSO}\ R_2\ \text{ALSO}\ \ldots\ \text{ALSO}\ R_n \qquad (2)$$

3. Fuzzy Model: Corrosivity Potential (CoP) vs. Soil Properties

The proposed fuzzy model is essentially a qualitative model that is constructed based on published work on the deterioration of pipes. Input variables are selected from soil properties such as soil resistivity, pH, redox potential, sulfide content and % clay. The output is *corrosivity potential* that is defined over a normalized interval of [0, 1], referring to *non-corrosive* and *highly corrosive* soils at two extremes, respectively.

A case study for the determination of *CoP* of cast iron pipes using the expert system is presented. Ductile iron pipes were not analyzed due to insufficient field data but nonetheless, this approach is equally applicable to these pipes as well. Table 2 shows the fuzzy rule base with five soil properties: soil resistivity, pH, % clay (soil particles with diameter < 0.002 mm) fines by weight, redox potential, and sulfide content. All properties, except the % clay fines, are the same as of those considered in the 10-P method. The % clay fines, which may account for moisture retention capacity, is substituted for moisture content. Soil types are defined in broad categories ranging from gravel to clay in terms of % clay fines as shown in Table 3. All input variables are partitioned into three fuzzy numbers *low* (L), *medium* (M), and *high* (H). The output is defined by five fuzzy numbers *very low* (VL), *low* (L), *medium* (M), *high* (H), and *very high* (VH). Each fuzzy number is specified by four edges of a trapezoid.

Table 2 Fuzzy rule base



Rule	RuleBase					
No	I1	I2	I3	I4	I5	O
1	L	L	LMH	LM	LMH	VH
2	L	L	LMH	H	LMH	H
3	L	MH	LMH	LM	LMH	VH
…	…	…	…	…	…	…
44	H	MH	MH	MH	L	VL
45	H	MH	MH	MH	MH	L

Table 3 Percent clay fines for different soil types

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

The fuzzy numbers of the input variables in some of the *antecedent* propositions are concatenated to reduce the number of the rules. For example, the fuzzy number MH in soil pH shows that the rule 3 corresponds to both *medium* and *high* pH. As a result, the number of rules for three 3-partition inputs is reduced to 45 (instead of 243 rules originally required). The linguistic variable LMH of an input variable in a rule implies that this input variable has no significant effect on the output for this specific rule.

The universes of discourse of the input variables are determined based on the minimum and maximum values of the soil properties, induced by the definition (e.g., pH) or obtained from published data. Naturally, the maximum and minimum values of a parameter with an infinite range cast into a range in which the parameter has an effect on the output. For example, a soil resistivity of greater than 5000 Ω-cm is unlikely to have an additional effect on *CoP*, so the maximum value of resistivity is taken to be 5000 Ω-cm.

Although *CoP* is defined in the interval [0 1], one cannot expect a defuzzified value for *CoP* greater than 0.774 (i.e., the center of area of the VH fuzzy number) and less than 0.033 (i.e., the center of area of the VL fuzzy number). It is noted that the defuzzified value is only a representative of the fuzzy output interval and this is not the limitation of the rules. More precisely, when the inferred fuzzy output is VH it means that *CoP* lies in the interval [0.5 1] and its best representative value is 0.774.

4. Deterioration Rate vs. Corrosivity Potential

Soil properties, pipe age, and maximum pit depth measurements available from a previous study on cast iron mains (Rajani *et al.*, 2000) are used to validate the fuzzy model. The corrosion pitting growth is used as a criterion for deterioration rates (*DR*). The soil properties and pit depth measurements are a snapshot of current conditions; and thus, deterioration rates obtained from maximum pit depth and pipe age, represent an average rather than maximum or instantaneous values. Table 4 shows a partial list of *DR* and *CoP* values for a series of soil samples.

Table 4 Field data and calculated corrosivity potential (*CoP*)

R Ω-cm	*pH*	Clay fines %	Redox potential mV	Sulfide presence	*DR* mm/yr	Corrosivity Potential (*CoP*)
590	7.7	30	-29	1	0.025	0.774
580	7.7	30	-30	1	0.042	0.774
1575	5.8	22	309	-1	0.044	0.339
5417	7.4	42	-42	-1	0.090	0.133
…	…	…	…	…	…	…
3100	6.3	42	306	0	0.033	0.199
1560	5.2	42	203	0	0.067	0.336
1300	7.6	22	-166	0	0.059	0.702
12929	4.6	22	268	0	0.027	0.185
6700	5.5	22	-88	0	0.055	0.300

Figure 1 shows the relationship between *DR* and *CoP* based on results obtained from the expert system. The plot suggests that the deterioration rate is "reasonably" correlated with *CoP*, i.e., the higher the *CoP* the higher deterioration rate will be. However, the data scatter in the figure can arise because of two reasons.

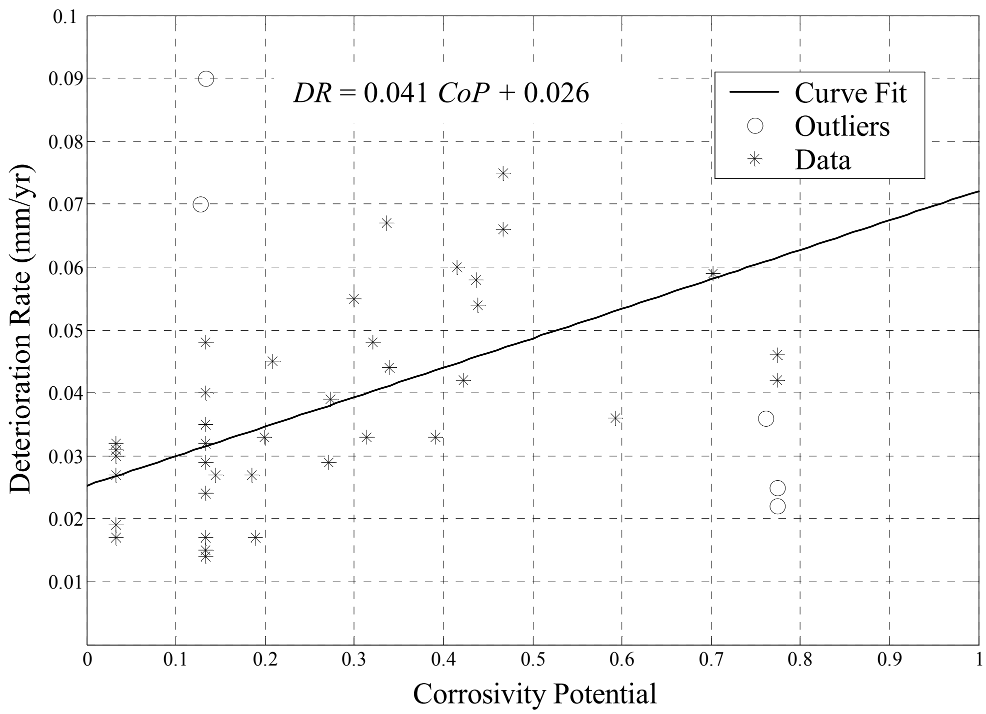


Figure 1 Correlation of deterioration rate with corrosivity potential

First, the fuzzy model is imprecise for a certain range of *CoP*. This could mean that either the number of fuzzy rules in the rule base is insufficient (i.e., the rule base does not satisfy the "completeness" condition), or the input and output partitions are not appropriately tuned in some range of their universe of discourse. Tuning up the model using field data, which will be addressed in future research, can alleviate these issues. Further, it could also mean that one or more input variables are dominant in certain ranges of *CoP*, which have not been considered. The identification of the other input variables is challenging because measurements of a variety of input candidates must be available before selecting the most pertinent ones. An expert survey can shed more light on other possible candidates for input variables.

Second, obvious outliers among the field data exist that must be excluded from the database used in objective modeling. An accurate pipe deterioration rate is typically unavailable because the deterioration rate is determined under the debatable assumption of an average (constant) corrosion rate from the installation to exhumation of the pipe. Also, the corrosion rate is obtained by measuring the maximum pit depth in a few pipe sections that are randomly selected. Consequently, the choice of the pit as well as the measurement techniques imposes a great deal of uncertainty on the measurements. Issues such as manufacturing defects, changing water table, backfill chemistry (e.g., addition of salt during winter, etc) and disturbance of backfill soil have an impact on the reliable determination of deterioration rates. For example, the first two rows of Table 4 refer to almost identical soil samples, yet the corresponding deterioration rates are significantly different. The outliers are shown with circles in Figure 1.

The relationship between the deterioration rate and *CoP* may be approximated using a linear model that is given by:

$$DR = m \cdot CoP + d \tag{3}$$

where m and d are the slope and intercept of the line, respectively. If the expected values of the slope and intercept are $\overline{m} = E(m)$ and $\overline{d} = E(d)$ then the estimated ranges are as follows:

$$\begin{aligned} m &= \overline{m} + \varepsilon_m \\ d &= \overline{d} + \varepsilon_d \end{aligned} \tag{4}$$

where ε_m and ε_d are the slope and intercept standard errors. Thus, for the linear relationship, the confidence interval for *DR* can be estimated using normally distributed slope and intercept. The equation of the line shown in Figure 1 is obtained based on the available data using the least squares method, which is given by,

$$DR = 0.041\, CoP + 0.026 \tag{5}$$

where the mean absolute error for this linear fit is approximately 0.08 and the coefficient of determination (R^2) is 0.34.

5. Conclusions

A fuzzy expert system is proposed to determine the deterioration rate of cast and ductile iron water mains based on the backfill soil properties. The expert system predicts a *corrosivity potential* (*CoP*) for a given soil sample and uses a linear regression model to link the *CoP* value to deterioration rate. The expert system yields not only a defuzzified value (crisp) of *CoP* but also an output fuzzy set in the form of a membership function, $\mu(CoP)$, which can be converted into a probability distribution under the *identity* and *monotonic* conditions. Either membership function or probability distribution can provide a reliable *CoP*.

Unlike the binary form of the corrosiveness measure (corrosive vs. non-corrosive) obtained from the 10-P method, *corrosivity potential* can be used to gauge the level of required corrosion protection. Specifically, the interval [0 1] of the *corrosivity potential* can correspond to the six levels of corrosion protection measures recommended for ferrous pipe materials (Dechant and Smith, 2004). A more rigorous approach to match the *corrosivity potential* with a specific corrosion protection measure would require cost-benefit analysis.

It is shown that corrosivity potential is "reasonably" correlated with the deterioration rate, according to the field data. As a result, the deterioration analysis is facilitated significantly by considering only one parameter affecting the deterioration of the pipes. Further, *corrosivity potential* can be used to perform a cost-benefit analysis and determine the optimal level of corrosion protection required in municipal infrastructure based on the soil properties.

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