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A Fuzzy Expert System for Deterioration Modeling of Buried Metallic Pipes

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Abstract – This paper presents the framework of a proposed expert system that is used to predict the deterioration rate of buried metallic pipes, based on surrounding soil properties. The knowledge base of the expert system is developed using two sources of information available for evaluating the deterioration of pipes: expert knowledge and field data. The novelty of the proposed approach lies in the modeling process and the framework of the expert system, complying with the nature of the information available.

The knowledge base is composed of a subjective and an objective model. The former is based upon fuzzy IF-THEN rules representing the expert knowledge obtained from published work and an expert survey. It determines the soil *corrosivity potential* (*CoP*). The objective model is a single-input-single-output (SISO) model that relates the deterioration rate (*DR*) to *CoP*. The objective model may be developed using either fuzzy modeling or a regression analysis of field data. The result of the latter based on a set of available field data (used in a previous study) is presented.

Keywords – Expert systems, fuzzy modeling, pipe deterioration, soil corrosivity

I. INTRODUCTION

Deterioration modeling of water mains is an essential practice to guide decision making in water main rehabilitation programs. In 2000, Water Infrastructure Network estimated that costs of deterioration for drinking water systems were \$20 billion in the United States only [1]. Water utilities use various criteria to assess the structural deterioration of pipes, among which are corrosion pitting rate and breakage frequency. 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. 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 [2] and Kleiner and Rajani [3] 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., [4] and Najjaran et al. [5]), primarily because available data are often qualitative and field data are either scarce or uncertain and vague.

Identification of potentially corrosive environments is a precursor to 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 a corrosive environment for existing pipes can save resources by focusing attention on the pipe sections that are at high risk [6,7]. Several techniques are currently used to assess conditions that are corrosive to buried pipes. The most common method is the 10-point scoring (10-P) that was introduced by CIPRA (Cast Iron Pipe Research Association, predecessor of DIPRA, Ductile Iron Pipe Research Association) in 1964 for cast iron pipes. The method was subsequently extended to ductile iron pipes [8]. The 10-P method uses five soil properties including

resistivity, pH, redox potential, sulfides, and moisture. The contribution of each soil property to corrosion is scored separately, and 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. 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.

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 $\mu(x)=0$, where $\mu(x)$ denotes the membership value of x . Fuzzy logic helps to address the inherent deficiencies of binary logic to account for uncertainties. Hence, fuzzy models can 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 might assign the soil as being 0.80 corrosive and 0.20 non-corrosive (depending on predefined qualitative scales of corrosivity). It is anticipated that corrosion protection measures can be selected more efficiently if the degree of soil corrosivity is considered. Further, the qualitative determination of deterioration rates can enhance risk assessment.

This paper presents the framework of an expert system to estimate pipe deterioration rates (based on maximum pit depth and pipe age) using a fuzzy model that relates pipe external corrosion to surrounding soil properties. Section 2 explains the structure of the proposed expert system. The results of a case study on a set of available field data are presented in Section 3. Section 4 presents the conclusions.

II. STRUCTURE OF THE EXPERT SYSTEM

An expert system estimates the current state or predicts the future state of a system using an a

priori model of the system. In this research, an expert system is developed to estimate the deterioration rate of metallic pipes using soil properties. Traditional expert systems were primarily meant to use information learnt from expert knowledge and mimic human decision making. Expert knowledge in deterioration modeling is formed upon theoretical knowledge and extended observations, which is general and often imprecise. Thus, it is required that the expert system extract additional information from the input-output data of a real system. Field data, obtained during the inspection, repair, or renewal of pipelines, are more specific but scarce and contain uncertainties, as it is impractical to collect field data on an entire water network. From this standpoint, fuzzy models seem like an appropriate choice as they can integrate the information provided by human experts and actual input-output data until a reliable knowledge base is developed.

The proposed fuzzy logic expert system consists of two modules: a knowledge base and an inference mechanism. The former includes a fuzzy model formed upon fuzzy IF-THEN rules. The latter uses fuzzy reasoning methods to process the knowledge base and deduce an output for instantaneous inputs. The modularized design of the expert system enables it to maintain a generic processing structure that is capable of dealing with various systems in different application domains (e.g., engineering, medical, financial, etc.) as long as the knowledge base is constructed in a compatible format. Another advantage of the modular design is that the expert system can be updated simply by expanding the knowledge base using new information as it becomes available over time. In other words, the knowledge base, unlike the inference mechanism, is open source and accessible to the users. The computation module and graphical user interface of the proposed expert system have been designed to comply with the aforementioned properties.

A. Knowledge Base

The knowledge base is essentially an *a priori* model that relates the pipe deterioration rate to the surrounding soil properties. The model consists of a subjective and an objective part.

The subjective model provides a fuzzy relationship between a number of soil properties

(perceived or proved factors) contributing most to the corrosion of metallic pipes, and a proposed corrosiveness criterion (viz., *corrosivity potential*, *CoP*). The subjectivity of the model is associated with the descriptive nature of *CoP*, and the fact that experts cannot always provide a quantitative relationship between the input and output variables in the model. In general, fuzzy rules can include uncertain antecedent and consequent propositions in which fuzzy quantities are associated with linguistic variables. The subjective model is generated using the direct approach of fuzzy modeling based on the expert knowledge obtained from published literature and an online expert survey [9].

The second part of the knowledge base is the objective model. Developing the objective model requires system identification that involves finding a model equivalent to the actual system with respect to input-output data acquired during nondestructive inspection of buried pipes or examination of exhumed pipes. The inputs of the objective model may be identical to the subjective model (i.e., soil properties), but the output cannot be the same because the model now requires a measurable quantity, such as breakage frequency or maximum pit depth. Thus, in order to fuse the two sources of information (expert knowledge and field data) and augment the subjective model using the field data, it is necessary to introduce a method to commensurate the two models.

Two approaches are proposed for the fusion of the two models. Fig. 1a shows the first approach in which the objective model is also an IF-THEN fuzzy model that is obtained by clustering the output space and then projecting the output clusters onto the input space [10,11]. In this approach the expert system directly determines the deterioration rate using soil properties. The subjective model provides an initial set of rules for an optimization process that minimizes the sum of the Euclidian distance between the output data and the center of the fuzzy clusters. Another fuzzy modeling technique is the template-based fuzzy modeling [12,13] in which the field data are used to assign credibility for individual rules, primarily defined by the subjective model. It is noted that if the data are noisy and the model is over-trained by the data, the

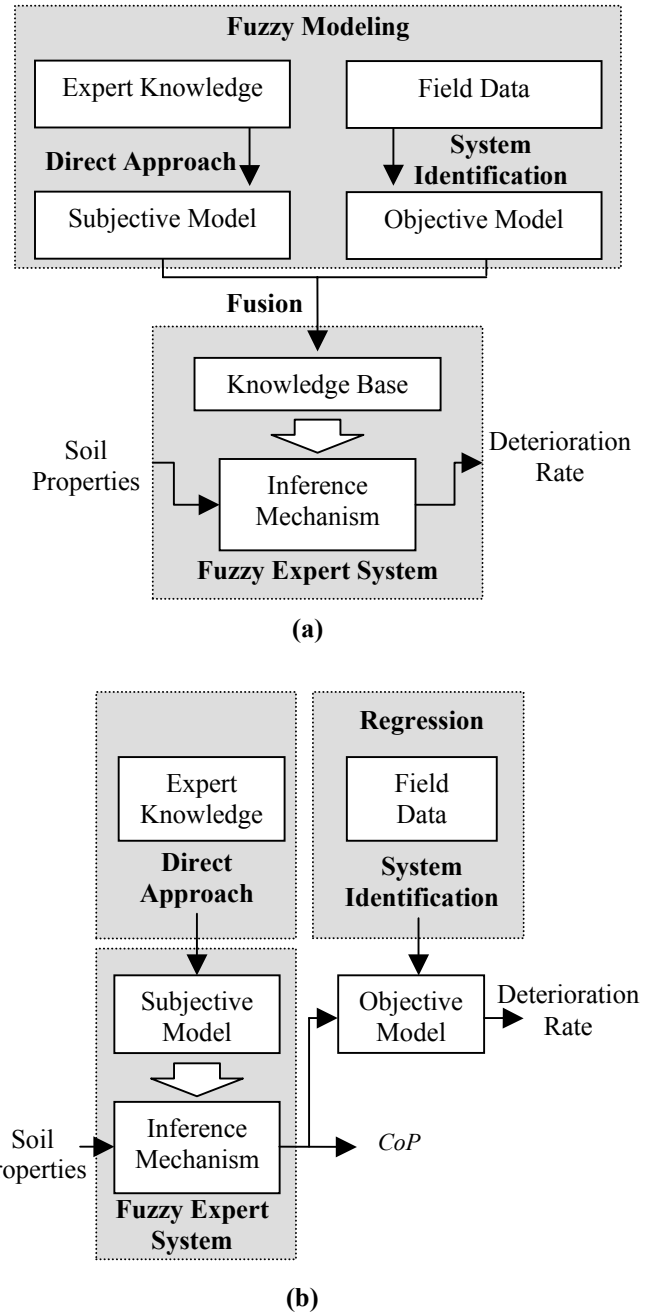


Fig. 1 The structure of the expert system **a)** fuzzy subjective and objective models **b)** a fuzzy subjective model and a regression objective model.

effect of expert knowledge will eventually vanish and a faulty model will be attained.

Fig. 1b portrays the second approach in which the expert system uses only the subjective model to determine the *CoP* of given soil samples. Then, the

field data are used to develop a regression model using the least squares method, which in turn relates the *CoP* to deterioration rate. The second approach has several advantages over the first approach. First, the modeling is much simpler and no complicated fuzzy clustering is required. Clustering is a nonlinear optimization process that may lead to local minima or partial optimal points, depending on the initial locations of the center of the output partitions. Second, the expert system provides not only a deterioration rate but also a descriptive *CoP* value that can help practitioners make more efficient decisions regarding the pipe protection means. Third, the expert knowledge, which is likely the most reliable source of information in this application, remains intact in the subjective model.

B. Inference Engine

The inference engine of the expert system include two fuzzy reasoning algorithms: Mamdani's reasoning [14] and logical reasoning [15], which use *minimum* and *product* operators as their *t-norm*, respectively. For the objective models developed using fuzzy modeling, one should choose the reasoning method that results in the closest fit to the field data. However, if the objective model is obtained by regression, the reasoning method may be chosen arbitrarily because the proximity of the field data and model is ensured by regression.

The output of the inference mechanism is a fuzzy subset in the output universe of discourse. The *defuzzification* of the fuzzy output is carried out using the *height method* [16]. In this method, the elements of the fuzzy output with a membership value of less than α are disregarded, and the defuzzified value is calculated using the center of area of the elements that have a membership grade of not less than α . The center of area (COA) and middle of maximum (MOM) defuzzification methods are special cases in which $\alpha = 0$ and $\alpha = \mu_{\max}(y)$, respectively, where $\mu(y)$ represents the output membership function in the output universe of discourse [12].

III. RESULTS

Soil properties, pipe age, and maximum pit depth measurements available from a previous study on

cast iron mains [17] are used to train the proposed expert system. 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. Deterioration rates are obtained by dividing the maximum pit depth by the pipe age under the assumption of a constant pitting growth rate over the life of the pipe. Therefore, deterioration rates represent an average rather than maximum or instantaneous values. This assumption provides a deterministic value for the deterioration rate and facilitates the regression analysis, but it also implies uncertainties to the objective model because issues such as manufacturing defects, changing water table, backfill chemistry (e.g., addition of salt during winter, etc.) and disturbance of backfill soil can change the pitting growth rate. Table 1 shows a partial list of *DR* and *CoP* values for a series of soil samples.

Table 1 Field data

R (Ω -cm)	pH	Clay fines %	Redox (mV)	Sulfide	DR (mm/yr)	<i>CoP</i>
590	7.7	30	-29	1	0.025	0.77
580	7.7	30	-30	1	0.042	0.77
1575	5.8	22	309	-1	0.044	0.33
5417	7.4	42	-42	-1	0.090	0.13
...	...	...	...	...	...	...
3100	6.3	42	306	0	0.033	0.19
1560	5.2	42	203	0	0.067	0.33
1300	7.6	22	-66	0	0.059	0.70
1292	4.6	22	268	0	0.027	0.18
6700	5.5	22	-88	0	0.055	0.30

Fig. 2 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*, higher the deterioration rate will be. However, the data scatter in the figure can arise because of two reasons.

First, the fuzzy model is imprecise in 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 have not been considered that may become dominant in certain ranges of *CoP*. The identification of additional 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.

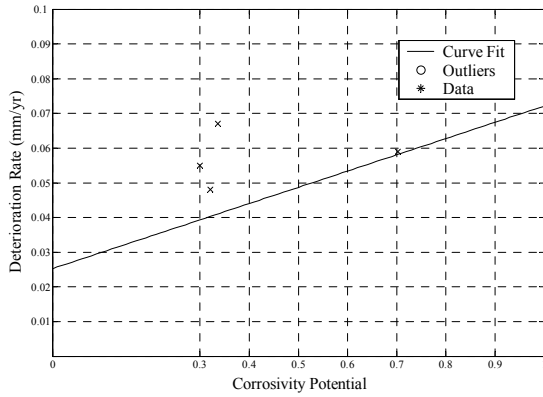


Fig. 2 Deterioration rate (*DR*) versus corrosivity potential (*CoP*).

Second, some of the points are appeared to be outliers that must be excluded from the database before used in objective modeling. For example, the first two rows of Table 1 refer to almost identical soil samples, yet the corresponding deterioration rates are significantly different. The outliers are shown with circles in Fig. 2. Outliers exist because an accurate pipe deterioration rate is typically unavailable. It is noted that the deterioration rate is determined under the debatable assumption of an average (constant) corrosion rate from the installation to exhumation of the pipe. Typically, measurement techniques are imperfect that in turn result in an erroneous maximum pit depth. Finally, the deterioration rate is calculated based on the maximum pit depth of a few pipe sections that are randomly selected and may not be a true representative of pitting growth rate.

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

$$DR = m \cdot CoP + d \quad (1)$$

where m and d are the slope and intercept of the line, respectively. If the expected values of the slope and intercept are $\bar{m} = E(m)$ and $\bar{d} = E(d)$, and ε_m and ε_d are the slope and intercept standard errors, the confidence interval for *DR* can be estimated using normally distributed slope and intercept. The equation of the line shown in Fig. 2 is obtained based on the available data using the least squares method, which is given by,

$$DR = 0.041 CoP + 0.026 \quad (2)$$

where the mean absolute error for this linear fit is approximately 0.08 and the coefficient of determination (R^2) is ≈ 0.34 . The result of curve fitting seems reasonable by considering the nature of the data and aforementioned uncertainties involved. However, more field data are required to improve the objective modeling process and determine a more rigorous relationship between the *corrosivity potential* and deterioration rate.

IV. 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 *corrosivity potential* (*CoP*) for a given soil sample and uses a linear regression model to relate 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, $\mu(CoP)$.

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 [18]. A more rigorous approach to match the *corrosivity potential* with a specific corrosion protection measure would require further research including cost-benefit analysis.

It is shown that *CoP* 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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