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A FUZZY-BASED MODEL TO DETERMINE CUI CORROSION RATE FOR CARBON STEEL PIPING SYSTEMS

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ABSTRACT

One of the most common external corrosion failures in petroleum and power industry is due to corrosion under insulation (CUI). Despite being external, ironically the challenges are in the prevention and detection. The difficulty in corrosion monitoring has contributed to the scarcity of corrosion rate data to be used in Risk-Based Inspection (RBI) analysis for degradation mechanism due to CUI. Limited data for CUI presented in American Petroleum Institute standard, (API 581) reflected some uncertainty for both stainless steels and carbon steels which limits the use of the data for quantitative RBI analysis. The objective of this paper is to present a fuzzy-based model to estimate CUI corrosion rate of carbon steel based on the API data. The fuzzy model has five inputs, which are operating temperature, type of environment, type of insulation, pipe complexity and insulation condition while the output in terms of CUI corrosion rate. The membership functions for both inputs and output will be discussed in details. A number of rules were used to perform defuzzification. After development of this fuzzy logic model, its root mean square error value (RMSE) and mean absolute deviation value (MAD) against API 581 data has also been checked, which revealed quite satisfactory results. The results from this model would provide corrosion engineers enough information about CUI corrosion rates concern to their plant so that they will be able to do necessary inferences in a more quantitative approach.

Keywords: corrosion under insulation, risk-based inspection, fuzzy logic model.

INTRODUCTION

One of the most serious external corrosion in petroleum and power industry is corrosion under insulation (CUI). CUI is a major concern that contributes to unexpected failures in many of today's plants. A study indicated that the highest incidence of leaks in the refining and chemical industries is due to CUI and not to process corrosion which causes between 40% to 60% of piping maintenance costs [1]. The failures can be disastrous or at least have an economic impact in terms of downtime and repairs [2].

By its very nature, CUI is very difficult to detect since corrosion occurs beneath the insulation, hence, making corrosion monitoring process very complicated. CUI typically tends to remain undetected until either the insulation and cladding/jacketing is removed during inspection period or when leakages occur. The difficulty in corrosion monitoring has contributed to the scarcity of CUI corrosion rate data to be used for quantitative Risk-Based Inspection (RBI) analysis. Most of the RBI deals with CUI qualitatively.

The data for CUI cases presented in the American Petroleum Institute (API) standard, (API 581) is limited and vague for both stainless steels and carbon steels [3]. The proposed corrosion rates are deterministic and subject to large uncertainty [3]. Various models have been developed to predict the failure progress. Among them data-driven models such as recurrent neural network [4] and fuzzy logic are mostly utilized by researchers. Since developing a neural network needs a large input data set, in case of having small size input data fuzzy logic is preferred. For these reasons, it seems like the best way to model corrosion rate due to CUI is by using fuzzy logic [5]. This paper will present a fuzzy-based model to estimate corrosion rate of carbon steel subject to CUI given the potential corrosive factors.

CUI CORROSION RATE BY API FOR CARBON STEEL

The relationship between corrosion rate of insulated carbon steels with operating temperature and type of environment is described by American Petroleum Institute in its standard, API 581 [6]. The type of environment is classified into four categories which are severe, marine, temperate and arid based on the average rainfall. The severe area is defined as area having more than 1500 mm/yr of rainfall, for marine area average rainfall is between 1000 to 1500 mm/year. For temperate area, the average rainfall is between 500 to 1000 mm/yr, whereas, the average rainfall for arid area is less than 500 mm/yr [7, 8]. Table 1 shows CUI corrosion rate in different type of environments at different temperatures, when type of insulation type is perlite or none while pipe complexity and insulation condition are average with the assumption that piping system are supported on beams or such a configurations that do not allow proper coating as per given by API 581. The plot of the relationships between corrosion rate with operating temperature and type of environment are shown in Figure-1 and Figure-2, respectively.

Based on both graphs (Figure-1 and 2) , it is shown that the highest corrosion rate for insulated carbon steel is 0.508 mm/yr at the operating temperature range between 32 °C to 71 °C in severe environment. The trends of the corrosion rates are quite consistent for all temperature ranges except for the range of 32 °C to 71 °C. For this temperature range the corrosion rate has been increased rapidly.

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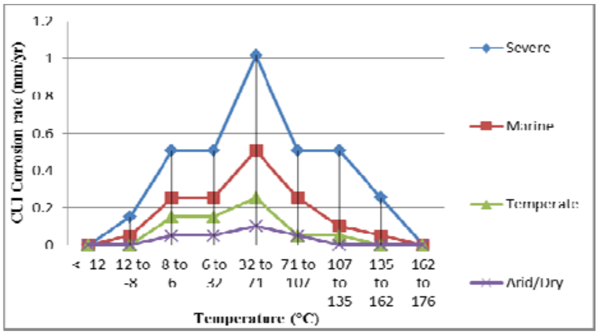

Figure-1. Relationship between CUI corrosion rate of carbon steel and operating temperature.

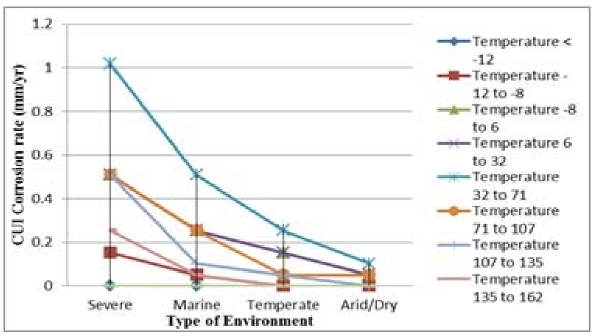

Figure-2. Relationship between CUI corrosion rate of carbon steel and type of environment.

Table-1. Relationship between corrosion rates with operating temperature and type of environment.

Operating Temperatur e (°C)	Corrosion Rate (mm/yr) in Different Types of Environments			
	Severe	Marine	Temperate	Arid / Dry
-12	0	0	0	0
-8	0.152	0.05	0	0
6	0.508	0.254	0.152	0.05
32	0.508	0.254	0.152	0.05
71	1.016	0.508	0.254	0.102
107	0.508	0.254	0.05	0.05
135	0.508	0.102	0.05	0
162	0.254	0.05	0	0
176	0	0	0	0

Note:

- Driver is defined as the atmospheric condition causing the corrosion rate.
- Interpolation may perform for intermediate values of temperature.

The relationships between corrosion rate and the two potential corrosive factors i.e. temperature & environment cannot be described as a simple relationship as in a traditional method like a linear or a exponential curve etc. Therefore fuzzy logic has been selected for this case.

FUZZY-BASED MODELING

Consider the meaning of a "high" CUI corrosion rate. Based on the API model discussed earlier, the highest CUI corrosion rate for carbon steel is 1.016 mm/yr. For corrosion engineer X, the high corrosion rate may be any value above 0.85 mm/yr. However, for corrosion engineer Y, the high corrosion rate maybe above 0.70 mm/yr. This "high" is called as a linguistic descriptor or variable which represents the imprecision existing in the system. The term "high" tells the same meaning to both engineers X and Y, but it is found that they both do not give a unique definition. The term "high" would be conveyed effectively, only when the given corrosion rate value is compared with the pre-assigned value of "high." The example shows the fuzziness of the definition of 'high'.

Relations are closely involved in fuzzy logic where they represent the mapping of the sets. Unlike classical relations where there are only two degrees of relationship between the elements of the sets, i.e., "completely related" and "not related", fuzzy relations have infinite number of relationships. Referring to the previous example, in classical relations, the "high" CUI corrosion rate is either "1" if it belongs to the set or "0" if it is not a member of the set. In the fuzzy relations, the "high" CUI corrosion rate can be formulated on an intensity scale. For instance, 0.90 mm/yr would be rated as "high" and 0.10 "low" (depending on predefined qualitative scales of corrosion rate).

A fuzzy logic model establishes the relationships between the output and inputs using a set of if-then rules as follow [9]:

R_i : If x_1 is A_{i1} and x_2 is A_{i2} and … x_j is A_{ij} Then y is B_i, for $i = 1, \ldots, n$ and $j = 1, \ldots, r$

where R_i represents the i th rule, n is the total number of rules, x_j are the input variables, y is the only output variable, A_{ij} are input fuzzy numbers defined in the input space and B_i is the output space number defined in the output space. Thus, every rule is a local fuzzy relationship that maps a part of the multidimensional input space into a certain part of the output space. Figure 4 shows graphically an input-output map for CUI fuzzy model.

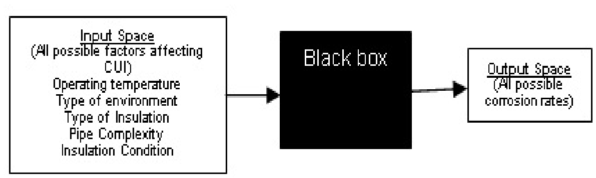

Figure-3. An input-output map for CUI corrosion rate.

CUI FUZZY MODEL

The assessment of CUI corrosion rate is often expressed vaguely by decision makers (for example, inspectors, inspection and corrosion engineers, regulators)

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that often translated into linguistic variables such as low, medium and high. A linguistic variable is a variable whose values are word rather than numbers. Based on the proposed fuzzy logic model, the CUI corrosion rate can be determined if type of environment, operating temperature, insulation type, pipe complexity and insulation condition are provided. Given the true numerical value is 1 and the false numerical value is 0, it indicates that fuzzy logic permits the value in-between, for example, 0.425 and 0.753. For example:

Q: At the operating temperature of 70 °C, is CUI likely to occur?
A: 1 (yes, or true)
Q: At the operating temperature of 150 °C, is CUI likely to occur?
A: 0 (no, or false)
Q: At the operating temperature of 50 °C, is CUI likely to occur?
A: 0.80 (for the most part yes, but not quite as much as at 70 °C)
Q: At the operating temperature of 100 °C, is CUI likely to occur?
A: 0.20 (for the most part no, but not quite as unlikely as at 150 °C)

Figure-4 shows the truth value of the occurrence of CUI if an absolute yes or no answer is forced to respond. On the other hand, Figure-5 shows the truth value of the occurrence of CUI if the fuzzy value is allowed. By making the plot continuous, the degree to which any given temperature belongs to the occurrence of CUI is defined, as shown in Figure-6 and Figure-7.

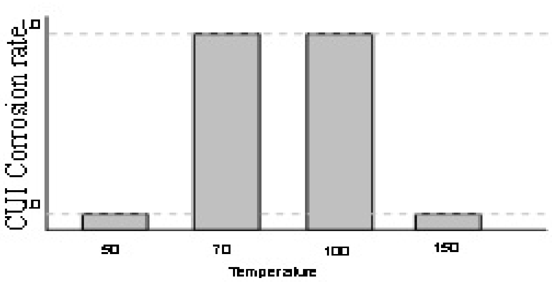

Figure-4. Classical relation.

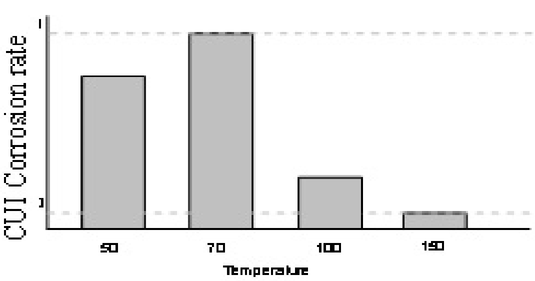

Figure-5. Fuzzy relation.

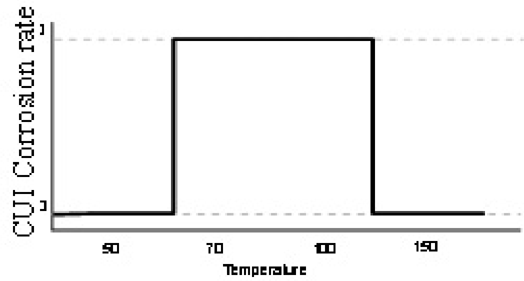

Figure-6. Continuous plotting of classical relation.

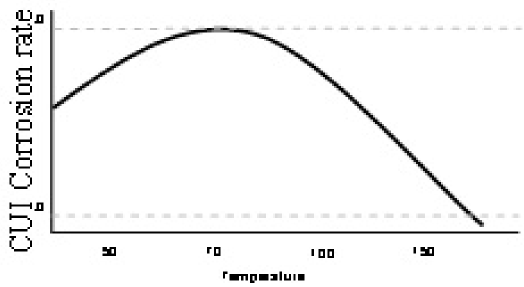

Figure-7. Continuous plotting of fuzzy relation.

Inputs and output

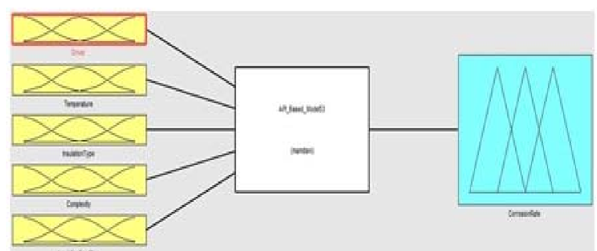

Figure-8. Number of inputs and output for CUI corrosion rate.

The proposed fuzzy model for CUI is constructed based on data published by API 581 Risk-Based Inspection Resource Document. The objective of the model is to assess CUI corrosion rate based on the input parameters which are type of environment, operating temperature, insulation type, pipe complexity and insulation condition as shown in Figure-3. The output is CUI corrosion rate which is defined over an interval [0, 2.0] mm/yr referring to the lowest and highest corrosion rate in API 581data. Figure-8 illustrates the fuzzy modeling accomplished using the Fuzzy Logic Toolbox in MATLAB R2013a [10].

Membership functions

A membership function is defined as a curve that describes how each point in the input space is mapped to a membership value (or a degree of membership) [10]. Number, type, linguistic variable and parameters values of membership functions are shown in Table-2.

ARPN Journal of Engineering and Applied Sciences

Table-2. Number, type and values of membership functions.

Operating Temperature (Input)			Pipe Complexity (Input)		
No. of Mem. Fn.	Linguistic Variable	Value	No. of Mem. Fn.	Linguistic Variable	Value
1	VVL	Less than equal to -8	1	Below	0 to 0.75
2	VL	−8 to 6	2	Average	0.75 to 1.0
3	L	6 to 32	3	Above	1.0 to 1.25
4	IL	32 to 71			
5	M	71 to 107			
6	IH	107 to 135			
7	H	135 to 162			
8	VH	162 to 176			
9	VVH	More than 176			
Insulation Condition (Input)			**Type of Environment (Input)**		
No. of Mem. Fn.	Linguistic Variable	Value	No. of Mem. Fn.	Linguistic Variable	Value
1	Below	1.0 to 1.25	1	Arid/Dry	0 to 508
2	Average	0.75 to 1.0	2	Temperate	508 to 1016
3	Above	0 to 0.75	3	Marine	1016 to 1524
			4	Severe	1524 to 2032
Type of Insulation (Input)			**CUI Corrosion Rate (Output)**		
No. of Mem. Fn.	Linguistic Variable	Value	No. of Mem. Fn.	Linguistic Variable	Value
1	Foamglass	0 to 0.75	1	VL	0 to 0.025
2	None , Pearlite	0.75 to 1.0	2	L	0.025 to 0.051
3	Fiber glass ,mineral wool, calcium silicate , asbestos	1.0 to 1.25	3	M	0.051 to 0.076
			4	H	0.076 to 0.127
			5	VH	0.127 to 0.254
			6	VVH	0.254 to 0.508
Gaussian type Membership function have been selected for all linguistic variables					

If-then rules

The if-then rule statements are used to formulate the relationships between the inputs and output. The rules are especially critical in producing the end result. There are altogether 972 rules which are being created. A sample of these rules is displayed in Table-3.

RESULTS AND DISCUSSION

The relationship of the inputs and the output was described using fuzzy logic assuming there are some ambiguous uncertainty and imprecision data brought out during model development. The input spaces for both inputs and output are determined based on the minimum and maximum values obtained from API 581. Table-4 shows the corrosion rate generated by the proposed model. The highest corrosion rate occurs at the temperature of 71°C, in the severe environment. The overall results obtained through proposed fuzzy logic model are much comparable with the API 581 data (root mean square error i.e. RMSE = 0.021 and Mean absolute deviation i.e. MAD = 0.104), with the added advantage of viewing the corrosion rate at each particular temperature. Figure-9 shows comparison of API 581 data versus proposed fuzzy logic model results.

Table-3. Rule base created in Matlab fuzzy logic showing relationship among inputs and output.

No. of Rules	When ***Driver*** is	and ***Temperature*** is	and ***Insulation Type*** is	and ***Pipe Complexity*** is	and ***Insulation type*** is	then ***CUI*** will be
1	Marine	VVH	NP	Below	Below	VL
2	Temperate	VVL	NP	Below	Below	L
2	Arid/Dry	L	NP	Below	Below	M
4	Arid/Dry	VH	FMCA	Average	Below	H
•	•	•	•	•	•	•
•	•	•	•	•	•	•
•	•	•	•	•	•	•
969	Severe	VVH	F	Above	Above	VL
970	Temperate	L	F	Below	Average	M
971	Severe	VVH	F	Above	Above	VH
972	Marine	VVL	FMCA	Above	Above	H
Where VVL : Very Very Low, VL : Very Low, L : Low, M : Medium, IH : Intermidiate High, H : High, VH : Very High VVH : Very very high, F : Foam glass, NP : None and Pearlite, FMCA : Fiberglass, Mineral wool, Calcium silicate and Asbestos						

A valueable point that can be stressed out from the proposed model is that at the operating temperature and type of environment where CUI is unlikely to occur, the corrosion rate is some numerical value. For instance at −12 °C and 176 °C in each type of environment, CUI corrosion rate given by API 581 is zero which is an unrealistic fact. It is claimed due to the reason that (i) if (for example) an insulated pipeline is in operation at −12 °C or 176 °C for 25 years, then it is not possible apparently or logically that it should not have CUI. (ii) According to statistics obtained from a local gas plant of Malaysia which has a marine environment, 2% of the operating temperatures of insulated pipelines are below −12 °C and 3% are above 176 °C. The proposed fuzzy logic model has a temperature range of -40 °C to 190 °C. It implies that the developed fuzzy logic model can also

ARPN Journal of Engineering and Applied Sciences

predict CUI corrosion rate at temperature range of below or more than -12 °C to 176 °C, for which API 581 is giving zero CUI corrosion rate. This minimum value of CUI corrosion rates can be used for further analysis such as remnant life determination of pipelines.

It should also be noted that predicted CUI corrosion rate are slightly exceeding the API 581 data. These a little bit higher CUI corrosion rates are admissible due to the reason that, apart from selected CUI producing factors/ inputs which have been taken in this study, there are also some other factors which are also responsible for the cause of CUI. Coating quality, pipe location, insulation jacketing condition, pipe support configurations etc. are some examples of these other factors. If these "other factors" are average or above average (in terms of worst scenario) in a case study then definitely CUI for that specific case will be more than the what published by API 581 data. Results obtained from proposed fuzzy logic model are already satisfying those type of situations expectedly, hence are facilitating RBI more appropriately.

Still, the model does not include "other factors" mention above,that may affect the rate of CUI. The authors are currently investigating those factors to be integrated into the proposed model.

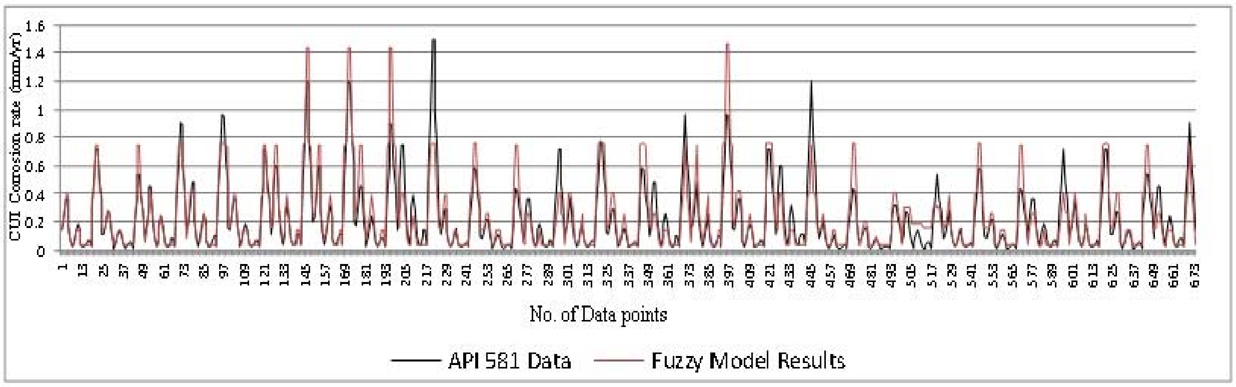

Figure-9. Comparison between CUI corrosion rates given by API 581 and fuzzy logic model.

Table-4. Comparison between CUI corrosion rates given by API 581 and fuzzy logic model.

Operating Temperature (°C)	Corrosion Rate (mm/yr) in Different Types of Environments							
	Severe		Marine		Temperate		Arid/Dry	
	API 581 data	Fuzzy logic Results	API 581 data	Fuzzy logic Results	API 581 data	Fuzzy logic Results	API 581 data	Fuzzy logic Results
-12	0	0.4822	0	0.1471	0	0.0787	0	0.0565
-8	0.152	0.6056	0.05	0.1864	0	0.0928	0	0.0472
6	0.508	0.6549	0.254	0.2979	0.152	0.1455	0.05	0.0476
32	0.508	1.2446	0.254	0.6334	0.152	0.3055	0.05	0.1005
71	1.016	1.2194	0.508	0.6508	0.254	0.2873	0.102	0.0923
107	0.508	1.1534	0.254	0.5504	0.05	0.1487	0.05	0.0832
135	0.508	0.6603	0.102	0.1813	0.05	0.0559	0	0.0477
162	0.254	0.5483	0.05	0.1046	0	0.0461	0	0.0459
176	0	0.1489	0	0.0593	0	0.046	0	0.0459

Note:

- Driver is defined as the atmospheric condition causing the corrosion rate.
- Interpolation may perform for intermediate values of temperature.

CONCLUSIONS

Corrosion under insulation (CUI) has been a major problem for oil and gas industries. As it remains hidden beneath the insulation so its accurate prediction, identification, and estimation is very difficult. A model for CUI was taken into consideration i.e. to predict CUI in terms of corrosion rate through fuzzy logic and then check its accuracy against the given API 581 CUI corrosion rates. The results from this model can be trusted considerably. The outcomes from this model would provide engineers to do necessary inferences in a more quantitative approach and eventually can be ascertained as a stunning tool for RBI.

REFERENCES

[1] G. Carbajal, A. Martinez-Villafane, J. Gonzalez-Rodriguez, and V. Castano, "Corrosion-resistant coatings: a nanotechnology approach," Anti-Corrosion Methods and Materials, vol. 48, pp. 241-245, 2001.

[2] M. M. Khan, A.A Mokhtar, and H. Hussin, "Prediction for corrosion under insulation subject to carbon steel pipes using anfis," ARPN Journal of Engineering and Applied Sciences, vol. VOL. 11, pp. 268-276, January 2016.

[3] A.A Mokhtar and M. Che Ismail, "A Fuzzy-Based Model to Determine Corrosion Rate for Carbon Steel subject to Corrosion under Insulation," paper presented at NACE, East Asia regional conference 2008, Kuala Lumpur, Malaysia, 2008, May.

[4] M. Muhammad, T. B. Mohammadreza, and Z. Karim, "Methodology for short-term performance prognostic of gas turbine using recurrent neural network," in Industrial Engineering and Engineering Management (IEEM), 2015 IEEE International Conference on, 2015, pp. 787-791.

[5] M. M. Khan, A. A. Mokhtar, and H. Hussin, "A Neural Based Fuzzy Logic Model to Determine Corrosion Rate for Carbon Steel subject to Corrosion under Insulation," Applied Mechanics and Materials, 2015, pp. 526-530.

[6] R. API, "581," Base Resource Document–Risk Based Inspection", American Petroleum Institute, Washington, DC., 2000.

[7] Stephen A. Anderson. "Corrosion under Insulation - Out of Sight. Out of mind," Hydrocarbon Engineering- Reprinted from August 2010.

[8] A. Wahizatul, S. Long, and A. Ahmad, "Composition and distribution of aquatic insect communities in relation to water quality in two freshwater streams of Hulu Terengganu, Terengganu," Journal of Sustainability Science and Management, vol. 6, pp. 148-155, 2011.

[9] H. Najjaran, R. Sadiq, and B. Rajani, "Modeling pipe deterioration using soil properties—An application of fuzzy logic expert system," in ACSE International Conference, 2004, pp. 1-10.

[10] Matlab. (2007). Fuzzy Logic Toolbox 2: User's Guide. Retrieved February 13, from http://som.yale.edu/unix/research_computing/pdf_doc/fuzzy/fuzzy_tb.pdf.