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PREDICTION FOR CORROSION UNDER INSULATION SUBJECT TO CARBON STEEL PIPES USING ANFIS

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ABSTRACT

Failures due to corrosion under insulation (CUI) are one of the most common external corrosion failures in petroleum and power industry. A small and inadequate amount of CUI corrosion rate data is available from literature and original plants. American Petroleum Institute (API) in its version API 581 has also given confined data for CUI which limits the use of the data for quantitative risk based inspection (RBI) analysis for both stainless steels and carbon steels. The aim of this paper is to construct and then checking the accuracy of an adaptive neuro fuzzy inference system (ANFIS) model along with predicting CUI corrosion rate of carbon steel based on, API data. The simulation shows that the model effectively predict the corrosion rates against the CUI corrosion rates given by API 581 with a mean absolute deviation (MAD) of 0.0006. The model is also giving CUI corrosion rates where API 581 is showing no value for it. The results from this model would provide the inspection engineers a satisfactory amount of CUI corrosion rate data which will be good enough for the quantitative approach of RBI.

Keywords: corrosion under insulation, risk-based inspection, adaptive neural based fuzzy inference system (ANFIS).

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 which causes between 40% to 60% of piping maintenance costs (H. Atmaca *et al*., 2001). The failures can be disastrous or at least have an economic impact in terms of downtime and repairs.

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 the insulation 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 RBI analysis. Most of the RBI deals with CUI qualitatively or semi qualitatively.

The data for CUI cases presented in the American Petroleum Institute (API) standard in its version API version 581 is very limited for both stainless steels and carbon steels. The proposed corrosion rates are deterministic and subject to large uncertainty. For these reasons, it is appropriate to model corrosion rates due to CUI by using a fuzzy logic technique. According to (H. Atmaca *et al*., 2001) among the other artificial intelligence techniques like neural network, fuzzy logic, Adaptive neural based Fuzzy Inference System (ANFIS), the ANFIS is more useful to overcome faster the complexity of the problem and it gives results with the minimum total error when compared to other techniques. This paper will present an adaptive neural based fuzzy logic model to estimate the 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 API 581. The type of environment is classified into four categories which are severe, marine, temperate and arid. The relationships between the corrosion rates with operating temperature and type of environment are shown in Table-1, Figure-1 and Figure-2. For the intermediate values of temperatures, interpolation may be performed (API 581, 2008).

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

Operating temperature (°C)	**Corrosion rate** (mm/yr)			
	Severe	**Marine**	**Temperate**	**Arid/Dry**
-12	0	0	0	0
-8	0.076	0.025	0	0
6	0.254	0.127	0.076	0.025
32	0.254	0.127	0.076	0.025
71	0.508	0.254	0.127	0.051
107	0.254	0.127	0.025	0.025
135	0.254	0.051	0.025	0
162	0.127	0.025	0	0
176	0	0	0	0

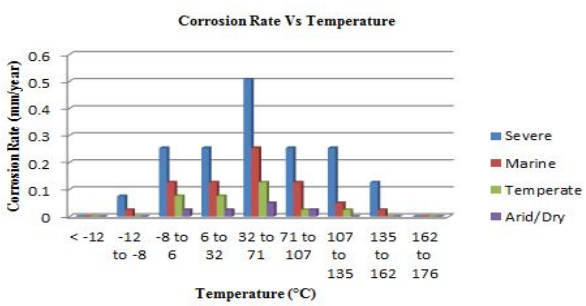

Figure-1. Relationship between CUI corrosion rate of carbon steel and operating temperature.

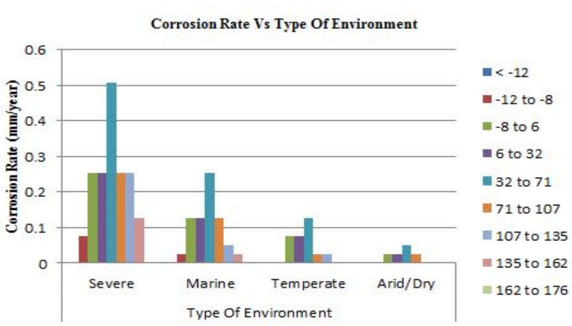

Figure-2. Relationship between CUI corrosion rate of carbon steel and type of environment.

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.

The relationships between corrosion rate and the two potential corrosive factors i.e. temperature and environment cannot be described as a simple relationship as in a traditional method. Therefore a fuzzy-based method has been selected for this case that is an adaptive neural based fuzzy inference system (ANFIS).

LITERATURE REVIEW

Corrosion under insulation (CUI) has been a major problem for the oil and gas industry for more than 40 years (Y.Wen *et al*., 2009).

Many researchers have used fuzzy logic for the prediction of different types of corrosion for alleviating the maintenance system of the industry with reference to the problem of corrosion. An overview of their efforts with reference to the corrosion and other related fields is presented here.

San He *et al*. (2012) anticipated the corrosion rate of L245NB steel in soil by utilizing Radial basis function Neural Network and Adaptive Neural-Fuzzy Inference System (ANFIS). Ahmet *et al*. (2009) studied that steel reinforcement corrosion within concrete is a standout amongst the most critical durability problems. He utilized neural network and ANFIS for predicting the compressive strength, splitting tensile strength and chloride ion permeability of concrete samples. He experienced that the

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ANFIS methodology gave a more exact results than neural network.

Yasin Hajizadeh (2006) conferred the problem of corrosion modelling from the hybrid neuro-fuzzy method. Mokhtar *et al*. (2011) presented a fuzzy-based model to estimate CUI corrosion rate of carbon steel based on the API data. That fuzzy model had two inputs, which were operating temperature and type of environment and the output in terms of corrosion rate. The results from that model provided engineers to do necessary inferences in a more quantitative approach. Maneesh Singh et al. (2009) presented a proposed methodology, based on fuzzy logic framework, for the establishment of an RBI program for pipes.

Wei Wu *et al*. (2013) developed a new model for risk analysis of corrosion failures of equipment based on fuzzy set theory. The results showed that this model was effective and feasible. YasinHajizadeh *et al*. (2007) used fuzzy logic to generate 3-D corrosion models for the purpose of predicting the corrosion. These models can be used as a powerful and reliable tool in decision-making processes by the managers and engineers. ElhamSa'idi *et al*. (2014) proposed a model for the risk of the process operations in the oil and gas refineries. The fuzzy logic system was proposed for risk modeling.

Y. Kleiner *et al*. (2006) presented a method to use the fuzzy deterioration model and the fuzzy risk for the effective management of failure risk. I. Bertuccio *et al.* (2012) make a combination of fuzzy logic theory and expert judgment to accomplish the modeling of the probability and severity of consequences and presented the possibility of the use of fuzzy logic to assess the risk of corrosion in natural gas pipelines.

Reza Javaherdashti (2012) discussed that microbiologically-influenced corrosion (MIC) is an unfamiliar type of corrosion. Using fuzzy logic, the two models were modified to define a fuzzy set of risks of MIC in catholically-protected pipes. S. Park *et al*. (2010) focused on the use of fuzzy logic techniques for damage prediction as applied to flat structures under corrosion conditions, by using a SHM (Structural Health Monitoring) approach. Ahmed Senouci *et al.* (2014) developed a fuzzy-based model to predict the failure type of oil pipelines using historical data of pipeline accidents.

Reza Javaherdashti (2013) investigated microbiologically influenced corrosion (MIC) risk, using fuzzy logics. He showed that fuzzy logics methods had the capability of showing how vulnerable a system could be to MIC. O.F. Aly *et al* (2012) developed a proposal for methodological software for modeling Stress Corrosion Cracking (SCC) based on the failure propensity plus a kinetic model. The main result is prediction with an adequate statistical regression. He uses Fuzzy Logic to determine the SCC-Propensity zones.

Reza Javaherdashti1 *et al*. (2012) developed a composite fuzzy function model to predict the corrosion resistance of duplex stainless steel in two environments; a biotic environment containing single-type corrosion-related bacteria iron reducing bacteria and a control, abiotic synthetic seawater environment. A. Martínez-Villafañeet al. (2010) used Electrochemical noise (EN) and fuzzy sets in order to predict the corrosion behavior of titanium alloys. Kleiner et al. (2006) described how the fuzzy condition rating of the asset is translated into a possibility of failure, that possibility of failure was combined with the fuzzy failure consequences to obtain fuzzy risk of failure throughout the life of the pipe.

Ali Jamshidi *et al*. (2013) performed an application of the fuzzy logic for modeling the uncertainty involved in the problem of pipeline risk assessment. Juhwan Kim *et al.* (2007) presented a decision making tool for ranking the condition of pipes with the available, inexpensive but vague or imprecise data using fuzzy logic. H. Fares *et al*. (2009) designed a framework to evaluate the risk of water main failure using hierarchal fuzzy expert system.

Thus it has been clear by the literature that many researchers have used fuzzy logic for the prediction of different types of corrosion but no one has used uptill for prediction of CUI. This is the gap which has been found within the literature review.

ANFIS MODELING

The application of fuzzy-based methods has considerably increased in recent years to solve many engineering problems where the available information is vague or uncertain (S. Sivanandam *et al*, 2007). The ANFIS modeling is one of the techniques of fuzzy based methods in which information is learned by the system from a data set.

ANFIS is an adaptive system that allows the utilization of neural network technique along with the fuzzy logic. It incorporates the qualities of both methods, as well as takes out a few impediments of their forlorn utilized cases. Operation of ANFIS looks like feed forward back propagation system. Subsequent parameters are registered forward while premise parameters are ascertained backward. There are two learning strategies in neural segment of ANFIS system: Hybrid learning system and back propagation learning system. In fuzzy area, just zero or first order Sugeno inference system or Tsukamoto inference system can be utilized (T. Takagi *et al*., 1985).

Since ANFIS aggregates both neural network and fuzzy logic, it is skilled of handling compound and nonlinear problems. Even if the objectives are not known, ANFIS could reach the finest results quickly. The architecture of ANFIS contains five layers and the number of neurons in each layer equals to the number of rules. In

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addition, there is no ambiguity in ANFIS as opposed to neural networks (Jang *et al*., 1997).

Figure-3 shows how ANFIS works with imprecise data and ambiguous information which so often encountered in real life to arrive decisions e.g. prediction for CUI corrosion rate.

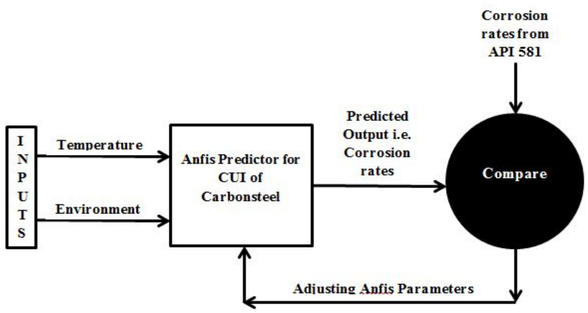

Figure-3. A block model for ANFIS working, for the prediction of CUI Corrosion rate.

CUI ANFIS MODEL

Inputs and output

The proposed ANFIS model for CUI is constructed based on the API 581 risk-based inspection resource document. The objective of the model is to assess CUI corrosion rate based on the input parameters. The input parameters are operating temperature and environment which are defined as [-20 190] and [1 2025] respectively as shown in Figure-4 and Figure-5, in the graphical user interface (GUI) of Matlab R2013a, while the output is CUI corrosion rate which is defined over an interval of [0 0.508] referring to the lowest and highest corrosion rate in API 581 which are 0 and 0.508 mm/yr respectively.

Initialization of the model

Through the GUI of ANFIS, the number and shape of inputs and the type of membership functions i.e. linear for the output of the model has been selected. As, a lot of data has been used to train this system that's why the system is too complicated. 9 and 4 membership functions have been assigned to each input i.e. temperature and environment respectively. The shape of the input membership function is selected as "guassmf" as shown in Figure-4 and Figure-5.

Training of the Model

API's given CUI corrosion rate has been divided into ratio of 70:30. 70% corrosion rates have been used as the training data for this model by using hybrid method while remaining 30% corrosion rates have been used for testing of this model.

Membership functions

A membership function is defined as a curve that describes how every point in the input space is drawn to a membership value (or a degree of membership) (Chang *et al*., 2005). For the input variable "operating temperature", the range of -20°C to 190°C is divided into nine membership functions which are Very Very Low (VVL), Very Low (VL), Low (L), Intermediate low (IL) Medium (M), Intermediate High (IH), High (H), Very High (VH) and Very Very High (VVH). The second input variable for this model is "type of environment" for which four membership functions have been selected which are Arid, Temperate, Marine and Severe as shown in Figure-4 and Figure-5.

In an ANFIS model there is no output membership function. As an alternative, there is a crisp number computed by multiplying each input by a constant and then summing up the results (Netto *et al*., 2013) this is all done in ANFIS automatically.

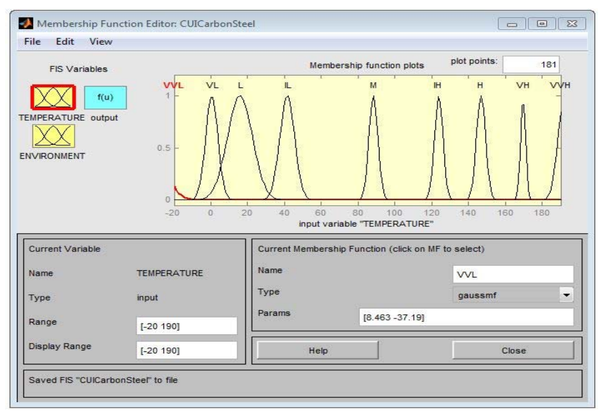

Figure-4. Operating temperature (input parameter 1).

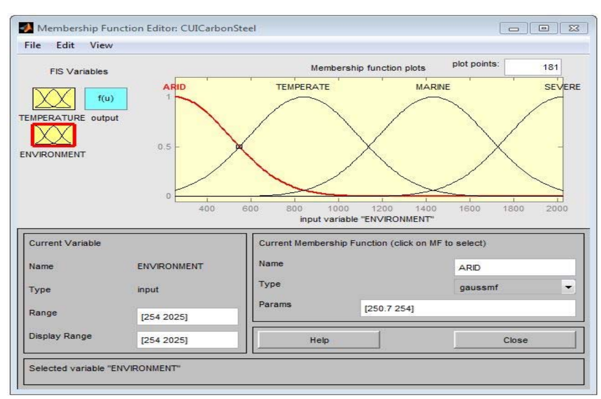

Figure-5. Type of environment (input parameter 2).

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If-Then rules

ANFIS itself created the if-then rule statements to formulate the relationships between the inputs and output. The rules are especially critical in producing the end result. There are altogether 36 rules which have been produced by the system.

DATA FLOW AND PROCESSING IN ANFIS FOR THE CUI ANFIS MODEL

As shown in Figure-6, a data containing file is loaded to the system for the purpose of training the model, then genfis is created in which the number and type of membership functions for both i.e. the input and output, are given to the system. Then before the system is commanded to train itself according to the provided data and membership function, the optimization method, error tolerance and number of epochs are given to the system. When the system is trained it is tested and then could be validated through the remaining 30% original data.

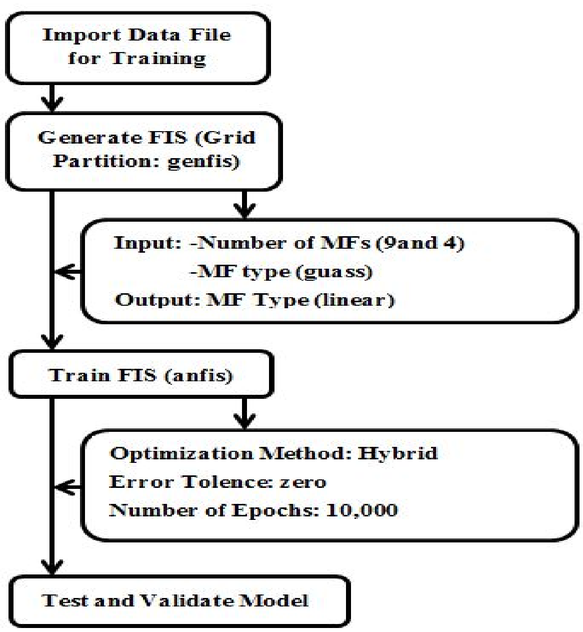

Figure-6. Data flow and processing in ANFIS model.

RESULTS AND DISCUSSIONS

The relationship of the two inputs i.e. temperature and environment and the output i.e. corrosion rate is described as the three dimensional relationship as shown in Figure-7. The results strongly depends on the number of rules, types and number of membership functions where any change in number of rules/membership functions will cause a great difference in results.

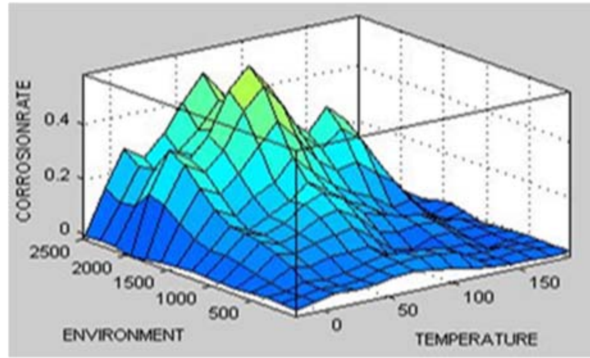

Figure-7. 3-D Relationships among operating temperature, environment and corrosion rate.

As it has been mentioned earlier that one of the aim of this paper is to also test the prediction accuracy of ANFIS modelingfor CUI corrosion rates against the corrosion rates given by API 581. Table-2 and Figure-8 shows the comparison between corrosion rates given by API 581and corrosion rates which arepredicted by the proposed model. Interpolation for API 581 data has been done by using MS Excel. The overall results are much comparable with the API 581 corrosion rates.

Another valuable point that can be emphasized from this proposed model is that, according to API 581 at the operating temperature and environment where CUI is unlikely to occur, the corrosion rate is some numeric value (like 0.004 mm/yr or 0.001 mm/yr at -12°C in a severe and marine environment respectively) instead of 0 mm/yr as given in API 581 data. This minimum values can be used for further analysis for instance remnant life determination of the carbon steel pipes, as according to the 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. It means that if temperature range of the proposed model is increased according to requirement then that model can also predict corrosion rates for 5% more operating temperatures for which API 581 is not giving any value of corrosion rates.

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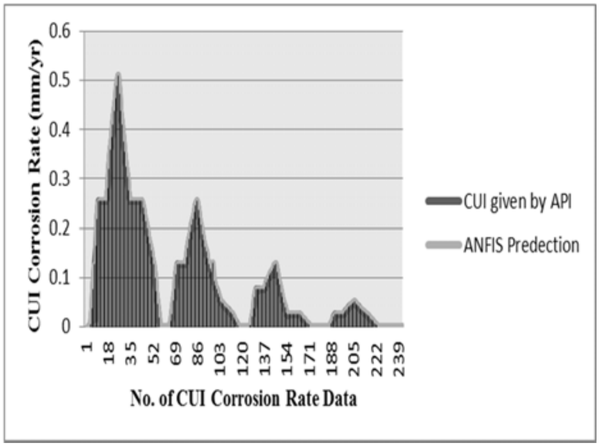

Figure-8. Comparison between CUI corrosion rates given by API 581 and ANFIS Model.

The constructed model is predicting its results in the form of corrosion rate with a MAD value of 0.0006 while having two corrosion factors i.e. temperature and environment as its inputs. In real plant, beside these two corrosion factors there are many other corrosionfactors which are also prominently responsible for the cause of CUI in carbon steel pipes. Pipe location, cladding condition, insulation condition, pipe complexity, pipe diameter, coating condition etc. are some of the most important examples of them. Since the generated model is predicting approx. same results as per API corrosion rates so on behalf of its existing results it can be expected that in future, if this model is fed with the data of the above mentioned or other related corrosion factors from the original plant, then this model will still predict much comparable results as it is handing presently.

In other words, when there will be six or seven input parameters (corrosion producing factors) for this ANFIS model instead of only two input parameters then it will still predict its single output (corrosion rate) within somehow same accuracy which is not possible by using other traditional prediction methods.

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 ANFIS 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 engineersto do necessary inferences in a more quantitative approach and eventually can be ascertained as a stunning tool for RBI.

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Table-2. Comparison between CUI corrosion rates given by API 581 and ANFIS Model.

		Type Of Environment							
Temperature Range (°C)	Temperature (°C)	Severe By Excell	Severe By ANFIS	Marine By Excell	Marine By ANFIS	Temperate By Excell	Temperate By ANFIS	Arid/Dry By Excell	Arid/Dry By ANFIS
<-12	-16	0	0.0007	0	0.0000897	0	0.0002	0	0.000084
	14	0	0.0008	0	0.0001	0	0.0006	0	0.0002
	-12	0.000	0.004	0	0.001	0	0.0004	0	0.001
-12 to -8	-10	0.038	0.037	0.013	0.011	0.000	0.002	0.000	0.0007
	-8	0.076	0.076	0.025	0.026	0.000	0.002	0.000	0.0006
-8 to 6	-4	0.127	0.126	0.054	0.053	0.022	0.021	0.007	0.007
	-1	0.165	0.0164	0.076	0.075	0.038	0.037	0.013	0.012
	3	0.216	0.217	0.105	0.106	0.060	0.06	0.020	0.019
	6	0.254	0.25	0.127	0.125	0.076	0.074	0.025	0.024
6 to 32	10	0.254	0.254	0.127	0.127	0.076	0.076	0.025	0.025
	16	0.254	0.254	0.127	0.127	0.076	0.075	0.025	0.025
	20	0.254	0.254	0.127	0.127	0.076	0.076	0.025	0.025
	24	0.254	0.254	0.127	0.127	0.076	0.076	0.025	0.025
	27	0.254	0.255	0.127	0.127	0.076	0.076	0.025	0.025
	32	0.254	0.255	0.127	0.127	0.076	0.076	0.025	0.025
32 to 71	36	0.280	0.28	0.140	0.14	0.081	0.081	0.028	0.027
	42	0.319	0.319	0.160	0.16	0.089	0.089	0.032	0.031
	48	0.358	0.358	0.179	0.179	0.097	0.097	0.036	0.035
	52	0.384	0.384	0.192	0.192	0.103	0.103	0.038	0.038
	56	0.410	0.41	0.205	0.205	0.108	0.108	0.041	0.04
	60	0.436	0.436	0.218	0.218	0.114	0.114	0.043	0.043
	64	0.462	0.462	0.231	0.231	0.119	0.119	0.046	0.046
	68	0.488	0.488	0.244	0.244	0.124	0.124	0.049	0.048
	71	0.508	0.508	0.254	0.254	0.127	0.127	0.051	0.05
71 to 107	76	0.473	0.473	0.236	0.236	0.112	0.112	0.047	0.047
	81	0.437	0.437	0.219	0.219	0.097	0.097	0.044	0.043
	85	0.409	0.409	0.205	0.205	0.085	0.085	0.041	0.04
	90	0.374	0.374	0.187	0.187	0.070	0.07	0.037	0.037
	93	0.353	0.353	0.176	0.176	0.061	0.061	0.035	0.035
	97	0.325	0.325	0.162	0.162	0.049	0.049	0.032	0.032
	100	0.303	0.303	0.152	0.152	0.040	0.04	0.030	0.03
	104	0.275	0.275	0.138	0.138	0.028	0.028	0.027	0.027
	107	0.254	0.254	0.127	0.127	0.025	0.024	0.025	0.025
107 to 135	110	0.254	0.254	0.119	0.119	0.025	0.025	0.022	0.022
	113	0.254	0.254	0.111	0.111	0.025	0.025	0.020	0.019
	116	0.254	0.254	0.103	0.13	0.025	0.025	0.017	0.017
	120	0.254	0.254	0.092	0.091	0.025	0.025	0.013	0.013
	123	0.254	0.254	0.084	0.083	0.025	0.025	0.011	0.01
	126	0.254	0.254	0.076	0.075	0.025	0.025	0.008	0.008
	129	0.254	0.254	0.068	0.067	0.025	0.025	0.005	0.005
	132	0.254	0.254	0.060	0.059	0.025	0.025	0.003	0.002
	135	0.254	0.254	0.051	0.051	0.025	0.025	0.000	0.00000066
135 to 162	138	0.240	0.24	0.048	0.048	0.022	0.022	0.000	0.0000012
	141	0.226	0.226	0.045	0.045	0.019	0.019	0.000	0.00000096
	144	0.212	0.212	0.042	0.042	0.016	0.016	0.000	0.00000072
	147	0.198	0.198	0.039	0.039	0.013	0.013	0.000	0.00000048
	150	0.183	0.183	0.036	0.036	0.010	0.01	0.000	0.00000023
	153	0.169	0.169	0.034	0.033	0.007	0.007	0.000	5.1E-09
	156	0.155	0.155	0.031	0.03	0.004	0.004	0.000	0.00000024
	159	0.141	0.141	0.028	0.027	0.001	0.001	0.000	0.00000049
	162	0.127	0.127	0.025	0.025	0.000	0.00002	0.000	4.7E-09
162 to 176 And More	165	0.100	0.099	0.020	0.019	0.000	0.000013	0.000	7.7E-09
	168	0.073	0.072	0.014	0.014	0.000	0.0000067	0.000	3.8E-09
	171	0.045	0.045	0.009	0.008	0.000	0.000000091	0.000	1.1E-10
	174	0.018	0.018	0.003	0.003	0.000	0.0000069	0.000	4.05E-09
	176	0.000	0.00001	0.000	0.000075	0.000	0.0000047	0.000	2.7E-09
	180	0.000	0.000006	0.000	0.0000093	0.000	0.00000051	0.000	3E-10
	183	0.000	0.000003	0.000	0.0000044	0.000	0.00000024	0.000	1.4E-10
	186	0.000	9.25E-08	0.000	0.00000045	0.000	0.00000003	0.000	1.7E-11
	190	0.000	0.0000038	0.000	0.000007	0.000	0.00000039	0.000	2.3E-10

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REFERENCES

[1] H. Atmaca, B. Cetisli, and H. S. Yavuz, "The comparison of fuzzy inference systems and neural network approaches with ANFIS method for fuel consumption data," in Second International Conference on Electrical and Electronics Engineering Papers ELECO, 2001.

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

[3] R. API, "581 Risk-Based Inspection Technologies," September 2008, 2008.

[4] "T.Takagi and M. Sugeno.Fuzzy identification of systems and its applications to modeling and control. IEEE Transactions on Systems, Man, and Cybernetics, 15:116-132, 1985."

[5] "Y. Tsukamoto, An approach to fuzzy fuzzy reasoning method. In M.M. Gupta, R.K. Ragade, and R.R. Yager,editors, Advances in fuzzy set theory and applications, pages 137-149. North-Holland, Amsterdam, 1979.

[6] "J.S.R. Jang and C.T. Sun and E. Mizutani.Neuro-Fuzzy and Soft Computing. Prentice Hall. 19:510-514. 1997." "Fuzzy Logic Toolbox User's Guide - MathWorks."

[7] W. Wu, G. Cheng, H. Hu, and Q. Zhou, "Risk analysis of corrosion failures of equipment in refining and petrochemical plants based on fuzzy set theory," Engineering Failure Analysis, vol. 32, pp. 23-34, 2013.

[8] M.-K. Chang, R.-R.Chang, C.-M.Shu, and K.-N. Lin, "Application of risk based inspection in refinery and processing piping," Journal of Loss Prevention in the Process Industries, vol. 18, pp. 397-402, 2005.

[9] T. Netto, H. Honorato, and R. Qassim, "Prioritization of failure risk in subsea flexible pipes via data envelopment analysis," Marine Structures, vol. 34, pp. 105-116, 2013.

[10] T. Takagi and M. Sugeno, "Fuzzy identification of systems and its applications to modeling and control," Systems, Man and Cybernetics, IEEE Transactions on, pp. 116-132, 1985.

[11] M. Singh and T. Markeset, "A methodology for risk-based inspection planning of oil and gas pipes based on fuzzy logic framework," Engineering Failure Analysis, vol. 16, pp. 2098-2113, 2009.

[12] Y. Wen, C. Cai, X. Liu, J. Pei, X. Zhu, and T. Xiao, "Corrosion rate prediction of 3C steel under different seawater environment by using support vector regression," Corrosion Science, vol. 51, pp. 349-355, 2009.

[13] Y. Hajizadeh, "Fuzzy corrosion modeling, new horizons, new opportunities," in SPE Eastern Regional Meeting, Canton, Ohio, USA, 2006, pp. 11-13.

[14] E. Sa'idi, B. Anvaripour, F. Jaderi, and N. Nabhani, "Fuzzy Risk Modeling of Process Operations in the Oil and Gas Refineries," Journal of Loss Prevention in the Process Industries, 2014.

[15] Y. Kleiner, B. Rajani, and R. Sadiq, "Management of failure risk in large-diameter buried pipes using fuzzy-based techniques," in 4th International Conference on Decision Making in Urban and Civil Engineering, 2004.

[16] I. Bertuccio and M. B. Moraleda, "Risk assessment of corrosion in oil and gas pipelines using fuzzy logic," Corrosion Engineering, Science and Technology, vol. 47, pp. 553-558, 2012.

[17] R. Javaherdashti, "A fuzzy approach to model RISK of MIC in a cathodically-protected pipe," Anti-Corrosion Methods and Materials, vol. 47, pp. 142-146, 2000.

[18] A. Senouci, M. S. El-Abbasy, and T. Zayed, "Fuzzy-Based Model for Predicting Failure of Oil Pipelines," Journal of Infrastructure Systems, 2014.

[19] R. Javaherdashti, "Modeling microbiologically influenced corrosion of N-80 carbon steel by fuzzy calculus," Metallurgical and Materials Transactions A, vol. 35, pp. 2051-2056, 2004.

[20] O. F Aly, M. MattarNeto, and M. MAM Schvartzman, "Stress Corrosion Prediction Modeling Software-A Proposal," Recent Patents on Corrosion Science, vol. 2, pp. 112-117, 2012.

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[21] Reza Javaherdashti, C. Nwaoha, and E. E. Ebenso, "Fuzzy Prediction of Corrosion Resistance of Duplex Stainless Steel to Biotic Iron Reducing bacteria and Abiotic Synthetic Seawater Environments: A Phenomenological Approach towards a Multidisciplinary Concept," International Journal of Electrochemical Science. vol. 7, 2012.

[22] Y. Kleiner, B. Rajani, and R. Sadiq, "Failure risk management of buried infrastructure using fuzzy-based techniques," Journal of Water Supply: Research & Technology-Aqua. vol. 55, 2006.

[23] A. Jamshidi, A. Yazdani-Chamzini, S. H. Yakhchali, and S. Khaleghi, "Developing a new fuzzy inference system for pipeline risk assessment," Journal of Loss Prevention in the Process Industries, vol. 26, pp. 197-208, 2013.

[24] J. Kim, C. Bae, and S. Park, "Evaluation of Deteriorated Water Pipes by Fuzzy Logics," 한국지능시스템학회국제학술대회발표논문집. pp. 349-353, 2007.

[25] H. Fares and T. Zayed, "Risk assessment for water mains using fuzzy approach," in Building a sustainable future—proceedings of the 2009 construction research congress, ASCE, 2009, pp. 1125-1134.

[26] Mokhtar, A.A. and he Ismail, M. (2010).Probabilistic reliability assessment of an insulated piping in the presence of corrosion defects. Journal of Applied Sciences. doi:10.3923/jas.2011.

[27] San. He, Y. Zou, D. Quan, and H. Wang, "Application of RBF neural network and ANFIS on the prediction of corrosion rate of pipeline steel in soil," in Recent Advances in Computer Science and Information Engineering, Ed: Springer, 2012, pp. 639-644.