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Effect of heterogeneities on pitting potential of line pipe steels: An adaptive neuro-fuzzy approach

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ABSTRACT

The variations in microstructure of line pipe steel (Grade X60) lead to significant changes in its corrosion behavior. Use of any particular steel for a given environment needs a robust data bank through which life predictions of components can be made confidently to avoid catastrophic failure. In the present endeavor, an adaptive neuro fuzzy based model is proposed to study the effect of microstructural variation on the performance of the candidate steel. This model has been verified with the experimental findings. The developed model will be a useful tool to justify the acceptance/rejection of the alloy on a commercial scale.

1. Introduction

Low/medium carbon seamless steel pipelines are used for water injection in petroleum industries. In a majority of the cases, sea water is used for this purpose after de-oxidation. Water pressure is maintained at ~100 kg/cm^2 and the pipelines experience ambient temperatures. The Carbon steel used has a normalized microstructure with strength of ~52–60 ksi. The outer surface of the pipes are coated and also cathodically protected to prevent damage against external corrosion; however, the inner surfaces are uncoated. It is a pre-requisite to obtain O_2 level ≤20 ppb during pressurized water injection to avoid pitting corrosion. However, at times the oxygen level shoots up and may reach as high as 2000–5000 ppb, which leads to pitting corrosion. The normal life of such pipes is ~15 years; but failures have been observed after 4–10 years of service. A Low velocity promotes under deposit corrosion with resultant leakage around the 6O'clock position. Inhomogeneous microstructure plays a dominant role in premature failures [1,2].

According to literature reports, the corrosion resistance of such steels is influenced by (a) the type of alloying elements and their distribution (b) the internal stresses due to different phases, (c) the variation in density of dislocation, (d) the thickness/compositional variation of passive film and (e) the type of heterogeneities in terms of phases along with their distribution. It is not only the micro-characteristics of the base alloy in terms of grain size, the nature of phases and different phase fractions, but the bulk heterogeneity also influences corrosion. The major heterogeneities in this category are different types of inclusions. Their nature, size distribution and area fraction control the degradation of pipeline steel. Information in this respect is mostly qualitative. It has been reported that amongst the inclusions, Ca and S containing inclusions are the most harmful [3–10].

A reliable prediction of the corrosion behavior is the fundamental step towards effective control of corrosion. Quantitative determination of pitting potential vis-à-vis microstructural parameters of line pipe steels is quite complex. Moreover, many of the factors act in a nonlinear fashion and can be opposed to the influence of another factor. This makes it difficult to develop an appropriate regression equation/functional relation from the various parameters. Probabilistic approaches are the most complex, requiring substantial amount of data for the proper development of the models. Artificial intelligence techniques like artificial neural networks (ANNs) and adaptive neuro fuzzy inference system (ANFIS) are efficient techniques to predict optimal conditions, because they do not need incorporation of any assumptions or simplifications. These methods attempt to mimic the ability of the human brain to learn patterns. A variety of different fuzzy modeling approaches have been developed and applied in engineering practice. The approaches provided powerful tools to solve complex nonlinear system modeling and control problems. ANFIS is designed and adapted to estimate wind farm efficiency [11–17], system identification [18] and process control [19].

Mohammad et al. [20] proposed a model to predict pitting corrosion using ANNs. However, one of the major shortcomings of ANNs is that, it needs a large amount of training data in order to acquire high learning precision. Fuzzy inference system (FIS) is a reasoning process that enables to map the hidden input-output relationship accurately. As fuzzy

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Table 1
As received X60 alloys: geometry and composition.

Steel	Geometry	C	Mn	S	P	Si	Cr	Ni	Cu	Ti	V	Nb	Mo	Al	N	Ca	B	Fe
Steel-1	Curved plate, thickness 14.1 mm	0.172	1.21	–	–	0.184	0.061	0.109	–	≤0.005	0.039	≤0.0005	0.02	0.03	–	–	–	Bal
Steel-2	Pipe, OD ~320 mm, thickness ~11.3 mm	0.15	0.33	–	–	1.17	0.061	0.03	–	0.0032	0.046	≤0.0005	0.006	0.043	–	–	–	Bal
Steel-3	Pipe OD ~450 mm, thickness ~14 mm	0.094	1.10	–	–	0.26	0.152	0.082	–	0.0056	0.068	0.022	0.104	0.034	–	–	–	Bal
Steel-4	Plate, thickness ~20 mm	0.073	1.49	0.001	0.007	0.265	0.204	0.032	0.015	0.01	0.002	0.042	0.010	0.027	0.0067	0.0017	0.0003	Bal
Steel-5	Plate, thickness ~11.1 mm	0.064	1.40	–	–	0.20	0.016	0.037	–	≤0.005	0.044	0.023	0.008	–	–	–	–	Bal
Steel-6	Pipe, OD ~450 mm, thickness ~7 mm	0.087	1.20	0.008	0.015	0.23	0.026	–	–	–	0.006	0.04	0.02	–	–	–	–	Bal

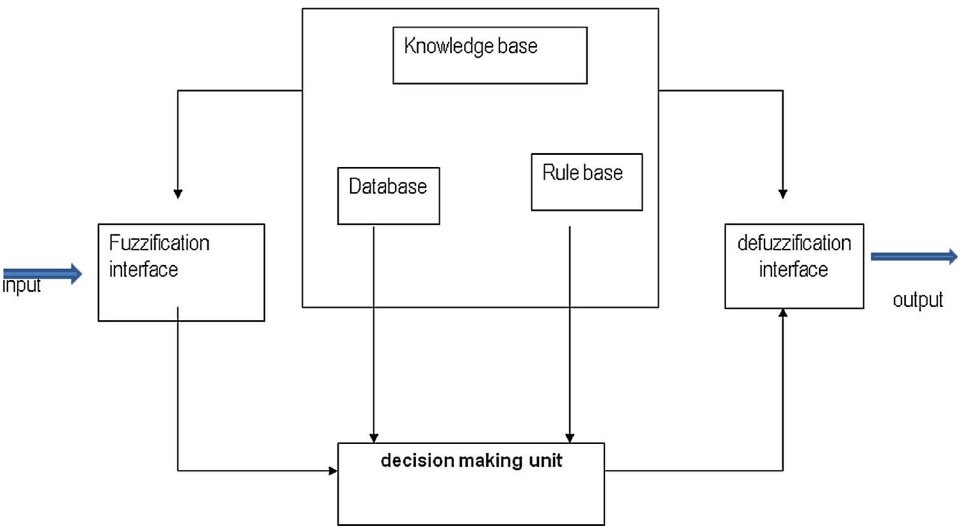

Fig. 1. A schematic of Fuzzy inference system.

Table 2
Crisp input variables used for various grades of line pipe steel.

Input	Steel-1	Steel-2	Steel-3	Steel-4	Steel-5	Steel-6
GS	12.0–13.8	12.45–13.7	12.1–13.9	11.8–12.6	12.85–10.9	13.7–11.3
Inc	0.06–0.09	0.11–0.17	0.06–0.14	0.06–0.6	0.08–0.19	5.06–0.07
AF	1.89–5.39	2.67–5.21	2.25–2.94	0.345–0.7496	0.6432–1.69	0.16–0.09
ComInc	60–76	47–27	64–86	49–72	55–70	49–35
AlInc	24–40	53–73	14–36	28–51	30–45	65–31
OutputPitting Potential (PP), mV	425–740	450–875	570–750	580–720	575–680	875–595

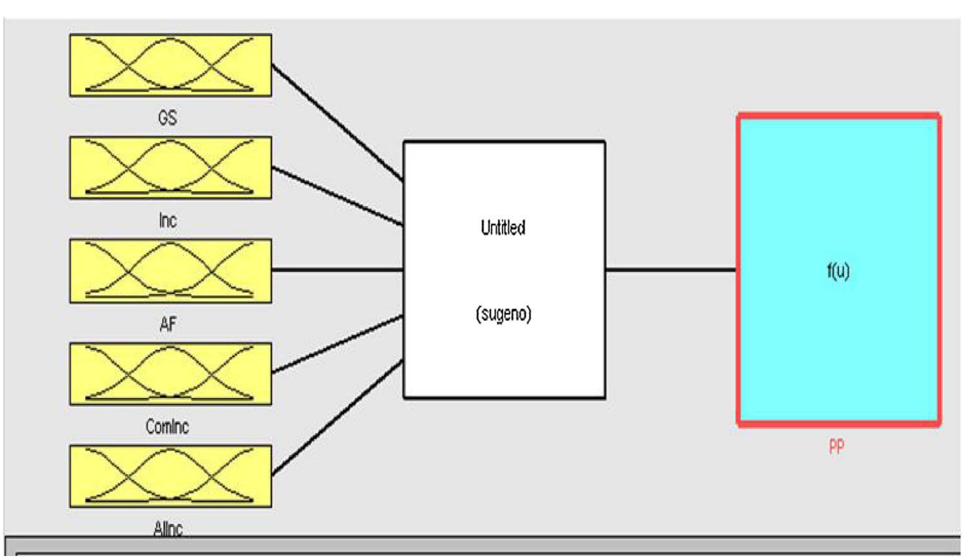

Fig. 2. Input/Output parameters for Fuzzy inference systems.