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Neural network modelling of high pressure CO_2 corrosion in pipeline steels

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ABSTRACT

The effect of carbon dioxide (CO_2) corrosion on pipelines is of great relevance to the petroleum as well as the Carbon Capture and Storage (CCS) industries. CO_2 corrosion is responsible for lost production as it brings about the gradual degradation of pipe internals with time. The cost of general corrosion is said to be between 3 to 5% of an industrialised nation's gross domestic product (Schmitt et al., 2009; Popoola et al., 2013). In the U.S., the cost of corrosion in the production and manufacturing sector was $34.4 billion in 2014, with the oil and gas industry accounting for more than half (Abbas, 2016).

The use of neural networks (NN) as an analytic tool for corrosion data has been established however the aim of this paper is to characterise selected Matlab transfer and training functions, and assess their degree of suitability for CO_2 corrosion rate prediction. Assessments of the training functions include the evaluation of the correlation coefficient (R^2-value) and determination of a cumulative absolute error to indicate the level of precision and the extent of model accuracy. A NN model is developed for predicting CO_2 corrosion at high partial pressures by considering the results of the various tests and analyses on the given Matlab functions. The results showed that the model is reliable with all test results falling within the 95% confidence limits. Leave-One-Out Cross-Validation (LOOCV) was implemented as a means for carrying out an additional assessment on model performance as well as for model selection from possible alternatives.

1. Introduction

Evidence from various analysed meteorological data suggests that the composition of the earth's atmosphere is changing and this is due to elevated concentrations of greenhouse gases such as carbon dioxide and methane, induced mostly by the anthropogenic combustion of carbonaceous fossil fuels (Tans, 2009). CO_2 is the most significant greenhouse gas given that its annual emissions have risen by almost 80% between 1970 and the 2000 s (Rao and Rubin, 2002; IPCC, 2014, 2007). As of 2010, it represented approximately 77% of total global emissions, rising up to the 400 ppm benchmark and surpassing this value in May 2013 (IPCC, 2014; Dlugokencky et al., 2014).

The global percentage share of CO_2 emissions by sector indicates that electricity (power) and heat generation is the chief emitter (~40%). Also, power plants are heavily reliant on coal hence carbon capture and storage (CCS) technologies will be most effectively deployed in this sector with the potential to significantly reduce CO_2 emissions by serving as a low-cost option (IEA, 2010; IPCC, 2014; World Energy Council, 2007).

In CCS deployment, CO_2 is captured at its source and transported via pipelines at elevated pressures in the supercritical region, as seen in the CO_2 phase diagram of Fig. 1. As a result of the very high pressures, there is a risk of pipeline corrosion (IEA GHG, 2010). This risk thus highlights the need for reliable corrosion behaviour prediction in order to control corrosivity (Cottis et al., 1999). Neural networks (NN) have been utilised for the analysis of a variety of corrosion data (Cottis et al., 1999; Owen et al., 2000). NNs use machine-learning algorithms to carry out non-parametric nonlinear regression of modelling data and as such offer more benefits in prediction than conventional polynomial and nonlinear regression techniques such as the ability to readily adapt to unknown functional forms (Owen et al., 2000; Beale et al., 2014). It also serves as a better method for knowledge acquisition (Radonja and Stankovic, 2002; Radonja, 2001). Another advantage of neural networks is that

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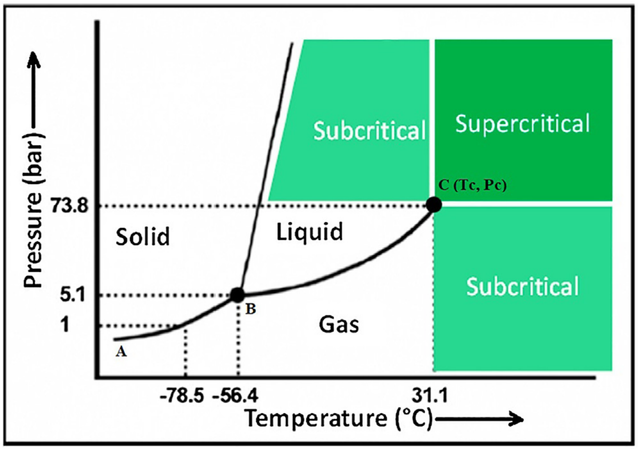

Fig. 1. Pressure-Temperature phase diagram for pure CO_2 (Laboureur et al., 2015).

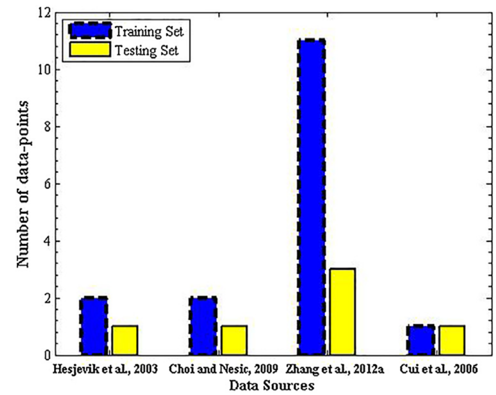

Fig. 2. Bar chart showing the distribution of data-points from each source.

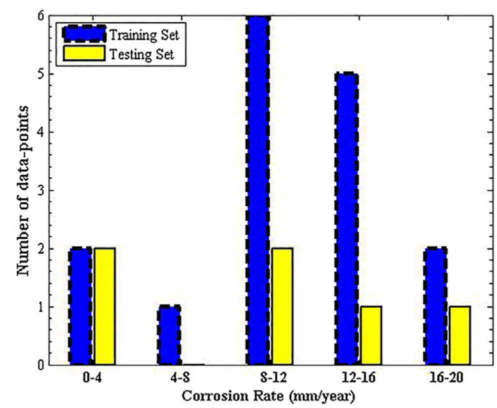

Fig. 3. Bar chart showing the distribution of data-points for the grouped magnitudes of Corrosion Rate.

they are particularly useful prediction tools even in scenarios where modelling data is sparse as is currently the case with high pressure CO_2 corrosion (Radonja and Stankovic, 2002; Choi and Nesic, 2009; Choi and Nesic, 2011; Choi et al., 2010).

In this paper, input data for the NN model was obtained from CO_2 corrosion studies of various sources in open literature (Choi and Nesic, 2009; Hesjevik et al., 2003; Zhang et al., 2012; Cui et al., 2006). This input data was gathered and divided into separate training and testing datasets for the purpose of model development. The log-sigmoid (logsig), hyperbolic tangent sigmoid (tansig) transfer functions and a set of six training functions were used in a series of tests (Beale et al., 2014; Vogl et al., 1988). The correlation coefficient and the sum of absolute error were calculated for each run to determine model accuracy (Draper and Smith, 1998; Sharma and Venugopalan, 2014). These results were then used as a basis for running initial tests to show general trends of performance of the given training functions and as a means for fine-tuning (pruning) the model parameters such as neuronal configurations best suited for high pressure CO_2 corrosion rate prediction.

2. Modelling

2.1. Training and testing data for NN modelling

Data from multiple sources in open literature was used in the neural network modelling of high pressure CO_2 corrosion (see Appendix A Tables A1 and A2 for raw data). All data sources determined corrosion rates experimentally by weight loss using autoclaves. For the Hesjevik et al. (2003) study, a Hastelloy C-276 (UNS N10276) nickel-alloy was used and for the Choi and Nesic (2009) study, an X65 carbon steel sample was used.

For the Zhang et al. (2012) study, several samples of steel were used, including a martensitic carbon steel, a pipeline X65steel as well as three chromium-containing corrosion-resistant alloys (CRA).

For modelling purposes, only carbon steel corrosion rate results were used in order to maintain consistency as corrosion rate measurements for CRA would affect the derived model. For the Cui et al. (2006) study, samples of P110, N80 and J55 carbon steels were used.

In total, there are 22 data-points and these were divided into training and testing sets with 16 and 6 data-points for each set respectively. The bar chart of Fig. 2 shows the distribution of the given data-points from each source.

Overall the number of data-points from Zhang et al. (2012) exceeds those of the other sources (63% share) due to the fact that the experimental corrosion rate results from this source were carried out for the widest range of temperatures (50–130 °C) and pressures (9.5–23.3 MPa).

For the other sources, corrosion rate tests were carried out by maintaining a constant temperature whilst varying pressures or maintaining a constant pressure while varying temperatures as is the case with Choi and Nesic (2009) and Cui et al. (2006) respectively. For the study by Hesjevik et al. (2003), tests were focused on measurement of corrosion rates for temperatures less than 30 °C. Experimental corrosion rate measurements were grouped into classes of 0–4, 4–8,. . ., 16–20 mm/year. Fig. 3 shows the distribution of corrosion rates in these classes.

From Fig. 3, the number of data-points for the mid-corrosion rate magnitude (8–12 mm/year) is greater than those for end-point corrosion rate groups (0–4 and 16–20 mm/year). The bar chart in Fig. 4 shows the distribution of data-points for the recorded experimental temperatures. There are more data-points in the mid-temperature readings (50 and 60 °C) than for end-point temperature readings (24 and 150 °C), as the former relates more closely to likely operating temperatures of pipelines than the latter.

Fig. 5 shows the corrosion rate-temperature profile for the training dataset. The median corrosion rate value was plotted for data-points with identical temperatures (see Appendix A, Table A1). A polynomial curve fit through the points depicts the classic peak observed for CO_2 corrosion rate as a function of temperature (De Waard and Lotz, 1993). It is noted that the range of corrosion rates in the mid-temperatures (50–80 °C) is ∼12 mm/year, highlighting that the greatest variation in the magnitudes of corrosion occurs over this temperature range.