

Chapter 1

Artificial Intelligence and Machine Learning in Corrosion Research

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ABSTRACT

Currently, the world is gradually moving to a digital world with the advent of artificial intelligence and machine learning models. The invention of these algorithms is a very big development for society. Artificial intelligence is a branch of science and engineering discipline concerned with teaching machines to think fast and operate like humans. Machine learning is concerned with using computer software to analyse complex non-linear tasks without the need for complex programming. In the oil and gas sector, the use of artificial intelligence and machine learning to appraise the efficiency of an inhibitor is gradually gaining attention in corrosion inhibition and pipeline integrity assessment. However, the proposed chapter will discuss more on the role of artificial intelligence and machine learning in corrosion related research.

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1.0 INTRODUCTION

In the chemical industry at large, metallic structures are susceptible to corrosion due to varying operating parameters existing within the system (Zheng et al., 2022). In the production of natural gas or oil refining, acidic gases not only degrade the gas quality but also pose operational difficulties for the downstream processes (Yazdi et al., 2022). Besides the normal corrosion caused by minerals acids due to pickling, descaling and acidization process, corrosion caused by dissolved CO₂ and H₂S in water and amine solutions have been found to cause serious havoc on the process equipment (Trausmuth et al., 2022; Anadebe et al., 2022a). However from the optimization and economic view point, the aim of every industry is to minimize cost of production and maximize profit, in this regards the use of artificial intelligence and machine learning models is a desirable development to avert future industrial hazards and economic loss.

Artificial intelligence (AI) is the ability of an artificial entity to solve complicated problems using its own intelligence. Artificial intelligence is focused with making computers behave more human-like and in a fraction of the time it takes a person to do it, while machine learning (ML) is an AI application that allows computers to automatically learn and grow from their experiences without having to be explicitly programmed. The goal of machine learning is to create algorithms that can analyze data and make predictions (Onukwuli et al., 2021; Ani et al., 2022). In view of these unique characteristics of AI and ML, they have found wide spread application in many areas such as science, health, financial institutions, engineering and more recent in academia. Many corrosion engineers have previously and currently using different models based on artificial intelligence and machine learning to make predictions on corrosion behaviour of metallic structures, inhibitor performance evaluation and pipeline integrity assessment (Abbas et al., 2018; Keprate et al., 2017). Li et al., 2021 modelled the corrosion rate of carbon steel in carbonated mixtures of MDEA-based solutions using artificial neural network. They used the corrosion rate data *via* weight loss to create a database for training and testing the ANN model. In their study they used max absolute relative deviation (MARD), to assess the performance of the ANN model. The developed 5-8-1 type ANN model was able to give a MARD value of 8.66%. The same corrosion rate database was utilized to develop the support vector machine (SVM) algorithm, in which radial basis function (RBF) was used as the kernel function, and K-fold cross-validation technique is applied to select the optimal model output. A comparison of performance in both training and testing shows that the developed ANN model outperforms the SVM model. Also, inhibitor performance of dexamethasone drug as corrosion inhibitor for mild steel in 2 M HCl electrolyte was appraised by (Anadebe et al., 2020). They proposed a multi input-single output (MISO) modeling based on adaptive neuro-fuzzy inference system (ANFIS). The operating parameters were acid concentration, inhibitor concentration, temperature and time. The developed ANFIS model accurately analysed the nonlinear interactions between the independent and dependent variables with coefficient of determination as high as R² 0.993. Similarly, Sanni et al., 2022 studied the application of hybrid machine learning models (ANN-ANFIS) to investigate the performance of agricultural waste as corrosion inhibitor for stainless steel type 904 in 0.5 M H₂SO₄. Their model's performance was evaluated based on statistical parameters such as correlation determination (R²), root mean square error (RMSE), mean absolute percentage error (MAPE), and mean absolute deviation (MAD). The results trend shows that the FCM-clustered ANFIS model with 20 clusters outperformed other models with MAPE, MAD, RMSE, and R² values of 1.9222, 0.5543, 0.7317, and 0.9308 at the testing phase respectively, and 0.5457, 0.3943, 2.9258 and 0.9993 at the training phase respectively. In another work by Aghaminiha et al., 2021, different machine learning models (artificial neural network, random forest, support vector machines, and K-Nearest neighbors) were used to model

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