Predicting the intergranular corrosion behaviour of 6000 series alloys using machine learning

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Abstract

The application of machine learning (ML) methods for accelerating the analysis and modeling of electrochemical measurement data, crack propagation and risk assessment in stress corrosion cracking, or resistance to local corrosion phenomena such as intergranular corrosion (IGC) and pitting has recently increased rapidly. [1-4] However, to enable accurate modeling and prediction, it is important to comprehensively define influencing factors and use high quality data. Factors influencing the microstructure and thus the degree of IGC in 6000 series alloys are related to the casting process [5,6], chemical composition [7-12], and thermomechanical history [6,12,13]. Unfortunately, complete or more systematic parameter sets are missing from the published literature on IGC. Furthermore, standards frequently used to test IGC in 6000 series alloys (ISO 11846 B and ASTM G110 [6-13]) allow for interpretation in terms of the test parameters, which can reduce comparability. [7,8] To address these challenges we leverage information from more than 135 individual tests to establish an accurate ML-based surrogate model capable of predicting the IGC penetration depth. The developed model leveraged Gaussian Processes to accurately link 17 different input parameters that include test standard procedures, heat treatments, as well as alloying elements to the IGC penetration depth. The resultant model can be generalized to new or unseen data, given its accuracy on a completely new set of 6000 series alloys with varying Cu content and heat treatments. This work illustrates the accuracy and high potential of using ML to close the gaps in systematic analysis and missing data. SNL is managed and operated by NTESS under DOE NNSA contract DE-NA0003525. SAND No. SAND2026-16422A

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