Predicting CP System Performance Of A Large Platform Complex Using Deep Neural Networks

Sami Abu-Zahra[1]

[1]Deepwater Corrosion Services Inc, Houston, Texas

Abstract

The design of a retrofit for offshore platforms requires an understanding of the historical service life of the platform. Platform service lives are measured in decades ranging between 20 to 40 years of service prior to retrofit. Over this period, multiple significant modifications to the existing structures such as additions of new structures connected by bridges and/or removal of significant sections of the platform may have occurred.
The primary challenge stems from the difficulty and associated cost in obtaining field data to use for calibration of the model. Cathodic protection surveys are generally performed every 3 to 5 years and consist of potential measurements taken on the structure using an ROV equipped with a portable reference electrode. On occasion, the anode depletion level will be visually estimated by the ROV operator on a select number of anodes with a grade between 1 and 4 corresponding to 25% depletion increments.

To resolve these events, a finite element model (FEM) of the facility was created and state variables were used to control any significant changes in the geometry of each of the platforms. Each of the seven structures were set up as separate components, and the eighth was used to model the electrolyte between the structures.

The Design Module was used to generate the geometry from a combination of 3D coordinates and imported CAD models. The Cathodic Protection physics was used to model the secondary current distribution between the anodes and cathodic surface areas. A surrogate model was created using Uniform Latin Hypercube sampling and 17 calibration parameters. A total of 8 components, 756 probes, 278 parameters, 3 designs of experiments (DOE) were required to complete the model.

To automate the creation of the geometry, associated probes, physics nodes, study creations, and result outputs the Application Builder was used as a framework to create custom methods for each of the repetitive operations. Taking in an array of inputs and the component name and automatically creating all the features required to construct and execute the model.

The primary model required over a 110 hours of computation time per tuple to run a fully time-stepped model for the historical life of the complex. However, individual structures could be run in parallel in less than 4 hours each. The usage of the Deep Neural Network (DNN) greatly decreased the number of iterations of the primary model required.

The optimization module used the trained DNN to rapidly estimate the 17 parameters and match them to the 144 observed values to create a predictive calibrated model of the complex that could then be used to design an optimal retrofit.

Reference

N/A