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Modelling the Corrosion Rate of Buried Pipes Using Modified Artificial Neural Network (MANN) Coupled with Monte Carlo Simulation

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors designed the study, implemented and wrote the manuscript. The first author wrote the final draft of the manuscript and managed correspondence. Both authors read and approved the final manuscript.

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ABSTRACT

Several researchers have developed models to predict corrosion rate in buried structures with good results using methods such as artificial neural networks, Monte Carlo to mention a few. This paper presents a novel approach to predicting corrosion rate in buried structures using Monte Carlo and a modified artificial neural network (MANN). Monte Carlo Simulation is used in this paper to estimate the probability of occurrence of uniform corrosion in buried steel pipes in different soil locations using the fixed walk method. The central limit theory and law of large numbers were utilised to reduce errors. While Modified Artificial Neural Networks was used to establish the relationships. Data used for this study were obtained from weight loss study of Nickel electroplated and non electroplatedAISI-1051 samples. The parameters measured were soil pH, soil temperature and atmospheric temperature of different soils taken from an oil producing site in Delta State, Nigeria. These parameters were assumed normally distributed. Corrosion Penetration Rate (CPR) was calculated for each scenario using the weight loss method. Relating these input

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parameters to the calculated CPR was possible via the employment of Modified Artificial Neural Networks, which makes use of the least square polynomial regression equations instead of the neuron box to avoid complexities in neuron number determination. Weights and Scaling factors were set appropriately to allow for easy convergence. Third degree polynomial equations were derived from the MANN and used as inputs for the MCS. Results from the MCS showed 80% correlation with data used and a reliable estimate for the CPR was achieved using this MCS-MANN approach. The CPR of the Nickel Electroplated Sample was less than zero which was in good agreement with the weight loss data. It is observed that the CPR values for Non-electroplated samples were 60% of the time higher than the values for electroplated samples.

Keywords: Uniform corrosion; Monte Carlo; artificial neural networks; steel pipes.

1. INTRODUCTION

The word Corrosion is derived from the Latin *corrosus* which means eaten away or consumed by degrees; an unpleasant word for an unpleasant process [1]. Corrosion is a spontaneous chemical reaction and is defined by the NACE as "The deterioration of a material, usually a metal, which results from a reaction with its environment" [2]. When corrosion occurs, these alloys are returned back to their natural states (ores). Corrosion cannot be totally eliminated so researchers have devised various programs to minimise corrosion growth rate, these include Cathodic Protection, Protective Coatings and Inhibitors. Pipelines play an extremely important role throughout the world as a means of transporting gases and liquids over long distances from their sources to the ultimate consumers but are subject to corrosion which causes it to disintegrate and weaken [3] incurring huge consequences.

Three different categories of consequences for corrosion failure have been identified as; safety, environmental and business/economic consequences [4]. Parametric and non-parametric models have been developed to predict the corrosion rate of pipelines. The General linear model [5] which established the baseline of external corrosion to be 2.65 mm/ lifespan for a 20 year design life, which is similar to the recommended values of PETRONAS Technical Standard of 3 mm/lifespan. Other attempts to estimate the corrosion rate for calculating re-assessment intervals using Monte Carlo method by considering the operating history of the pipeline and any knowledge of its condition such as prior in-line inspections or direct observations of corroded areas on the pipeline have also been made [6]. Monte Carlo simulation and degradation models have also been used to predict pipeline corrosion rates and also to establish the reliability of pipelines over a period of time [7]. The proposed methodology was fed and tested with field data acquired from 11 onshore O&G fields. Discrete random numbers were generated from historic data, yearly corrosion rate was estimated using Brownian random walk, Corrosion wastage were predicted (with linear and power models) and Mean Time For Failure (MTFF) of the pipelines were estimated during the course of the study. The conclusion of the author was that both the Monte Carlo Simulation and the degradation models can reasonably predict the pipeline corrosion rate.

However the level of complexity can serve as a medium for distinguishing Monte Carlo Methods; such as simple MCS and complex MCS [8]. A simple MCS is derived when the physical situation is stochastic in nature i.e. it involves probabilities such as transport of metal particles through material medium. While a complex MCS is derived when the physical situation is not stochastic.

The probability distributions of external corrosion, pit depth and pit growth rate were investigated in underground pipelines using Monte Carlo simulations by Caleyo and his co-workers [9]. The study combined a predictive pit growth model developed by the authors with the observed distributions of the model variables in a range of soils. It is pertinent to note that any of the three maximal extreme value distributions, i.e. Weibull, Fréchet or Gumbel, can arise as the best fit to the pitting depth and rate data depending on the pipeline age.

The consequence of corrosion has led many companies to enact measures to periodically assess their pipelines. Such assessments are often costly to execute annually, thus measures are taken to ensure they are carried out at intervals sufficiently short to prevent leaks or ruptures from metal loss on pipelines. Several approaches have been taken towards studying the effects of corrosion on buried steel pipes, however literature is sparse on the use of a probabilistic methods coupled with a Modified Artificial Neural network which provides the needed speed, accuracy and flexibility [8], which is the focus of this study.

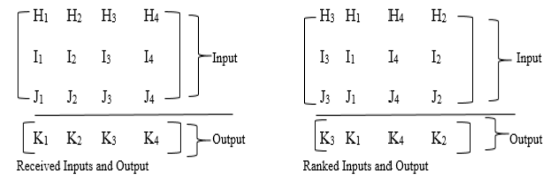
2. METHODOLOGY

2.1 Modified Artificial Neural Networks

From literature [10,11], Artificial Neural Networks have been used tremendously in various fields of industry and commerce. Their ability to "learn by example" and to generalise this knowledge so as to give correct predictions to previously unseen data makes them extremely attractive. Attempts have been made constantly to apply this method to corrosion prediction. Artificial Neural Networks can learn the behaviour of materials in various corrosive soil locations and predict their behaviour. Neural networks howbeit appealing exist with certain limitations, when applied without consideration of the potential sources of error. Inaccurate answers can be derived from neural networks which tend to be highly misleading in research when used with little or no caution.

While modelling the experiment in the MANN, the flow chart above is used and four cases were considered. The three inputs data were soil pH, soil temperature and atmospheric temperature. The first output is given as $\boldsymbol{K(H) = aH^3 + bH^2 + cH + d}$. The second input is modelled similarly which are used in generating the respective values of **a1**, **b1**, **c1 and d1**. The second output is thus given as $\boldsymbol{K(I) = a1I^3 + b1I^2 + c1I + d1}$. Third output is similarly $\boldsymbol{K(J) = a2J^3 + b2J^2 + c2J + d2}$ The final output is therefore the average of these values given as as: $\boldsymbol{K = (K(H) + K(I) + K(J))/3}$.

Where Hi, Ii, Ji and Ki (i = 1, 2, 3, 4) are valid inputs and output respectively, then the number of cross overs could be determined from the ranked output. The 2 cross over observed in the model, means that the data could be modelled using a polynomial of order 3 (i.e. a cubic equation). In modelling therefore, the following equations were used;



If $K_1 > K_3,\ K_1 > K4,\ K_2 < K_4$ (1)

$$\sum K_i = a * n + b\sum_{i=1}^{n} H_i + c\sum_{i=1}^{n} H_i^2 + d\sum_{i=1}^{n} H_i^3 \quad (2)$$

$$\sum K_i H_i = a\sum_{i=1}^{n} H_i + b\sum_{i=1}^{n} H_i^2 + c\sum_{i=1}^{n} H_i^3 + d\sum_{i=1}^{n} H_i^4 \quad (3)$$

$$\sum K_i H_i^2 = a\sum_{i=1}^{n} H_i^2 + b\sum_{i=1}^{n} H_i^3 + c\sum_{i=1}^{n} H_i^4 + d\sum_{i=1}^{n} H_i^5 \quad (4)$$

$$\sum K_i H_i^3 = a\sum_{i=1}^{n} H_i^3 + b\sum_{i=1}^{n} H_i^4 + c\sum_{i=1}^{n} H_i^5 + d\sum_{i=1}^{n} H_i^6 \quad (5)$$

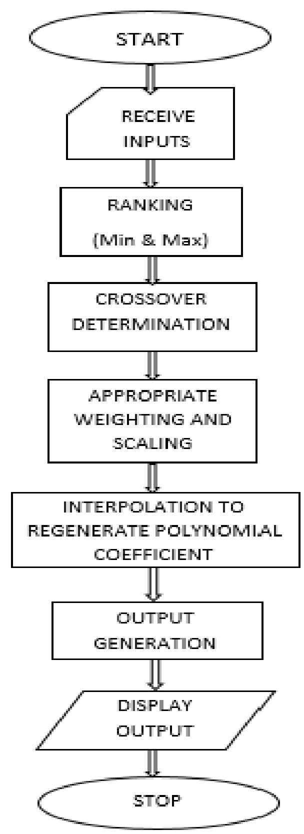


Fig. 1. MANN flow chart

The equations (2) to (5) are employed for all three input parameters (H, I, J) which is an expanded version of Fig. 2 below.

$$\begin{bmatrix} \sum K \\ \sum KH \\ \sum KH^2 \\ \sum KH^3 \end{bmatrix} = \begin{bmatrix} n & \sum H & \sum H^2 & \sum H^3 \\ \sum H & \sum H^2 & \sum H^3 & \sum H^4 \\ \sum H^2 & \sum H^3 & \sum H^4 & \sum H^5 \\ \sum H^3 & \sum H^4 & \sum H^5 & \sum H^6 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix}$$

Fig. 2. Least square matrix representation

2.2 Monte Carlo Simulation

Monte Carlo simulations MCS can be executed using certain required entities, such as; input distributions, relating equations and simplifying assumptions;

The input distribution was derived from an existing data [12]. While the relating equations are derived from the matrix output of the MANN, whose coefficients are however unique to each scenario studied, but layout remains consistent with the least square regression polynomial equation.

The simplifying assumption made for this model is that the measured input parameters are assumed to be normally distributed about a mean with a given standard deviation. The limit of accuracy of this assumption was assessed as shown in Figs. 4 and 5. It is observed that this assumption of normalcy lies within acceptable limits as there is little variance between plots shown in the various value distributions. The flow chart below in Fig. 3 represents the functioning of the Monte Carlo Simulation algorithm.

The soil samples were taken from five locations on the producing site namely; the tank farm, skimmer pit, export pump area, saver pit and the arrival manifold point designated as (location 1, 2, 3, 4 and 5 respectively.

3. RESULTS AND DISCUSSION

3.1 Simulating Experiment

The simulation experiment f was done using the MATLAB R2012b software. Results were obtained in the form of graphs (as depicted in Figs. 6-11, and Table 1). The experiment was executed on an *HP envy dv4* laptop, 8 GB RAM, 750 GB HDD and an Intel® Core™ i5-3210 CPU @ 2.50 GHz. IBM SPSS is used to provide descriptive statistics for the data source (Table 1).

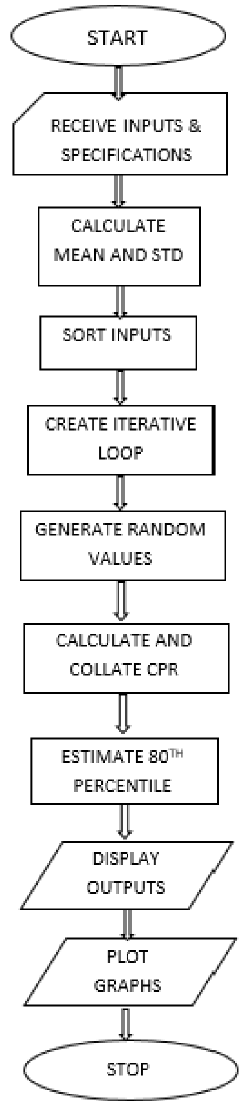


Fig. 3. MCS flow chart

3.2 Results

Based on the above described methodology, the MANN-MCS algorithm provided the following results described below. The input parameters are sorted and normally distributed about a mean at a standard deviation thus allowing for a less complex computation of the expected value. Little of no significant variation is noticed between the different sample input distributions however the sensitivity of this method captures the slightest variation in its analysis, thus providing different values for the relating equations. A substantial amount of the results had negative values as the expected values which mean a perceived increase in weight of the steel (negation of weight loss). But this is in agreement with the weight loss data used for this analysis.

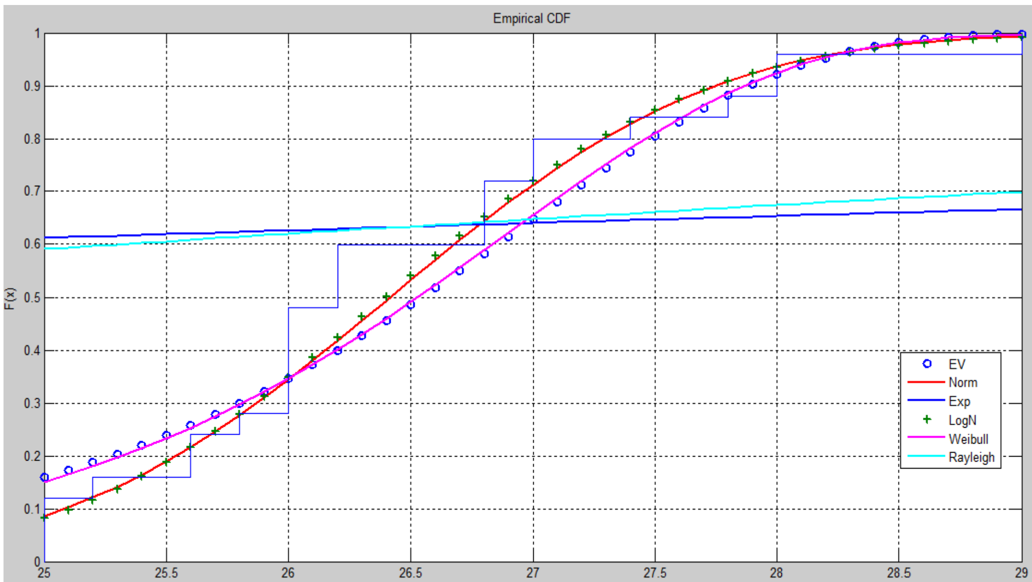


Fig. 4. Empirical CDF normalcy assumption validation

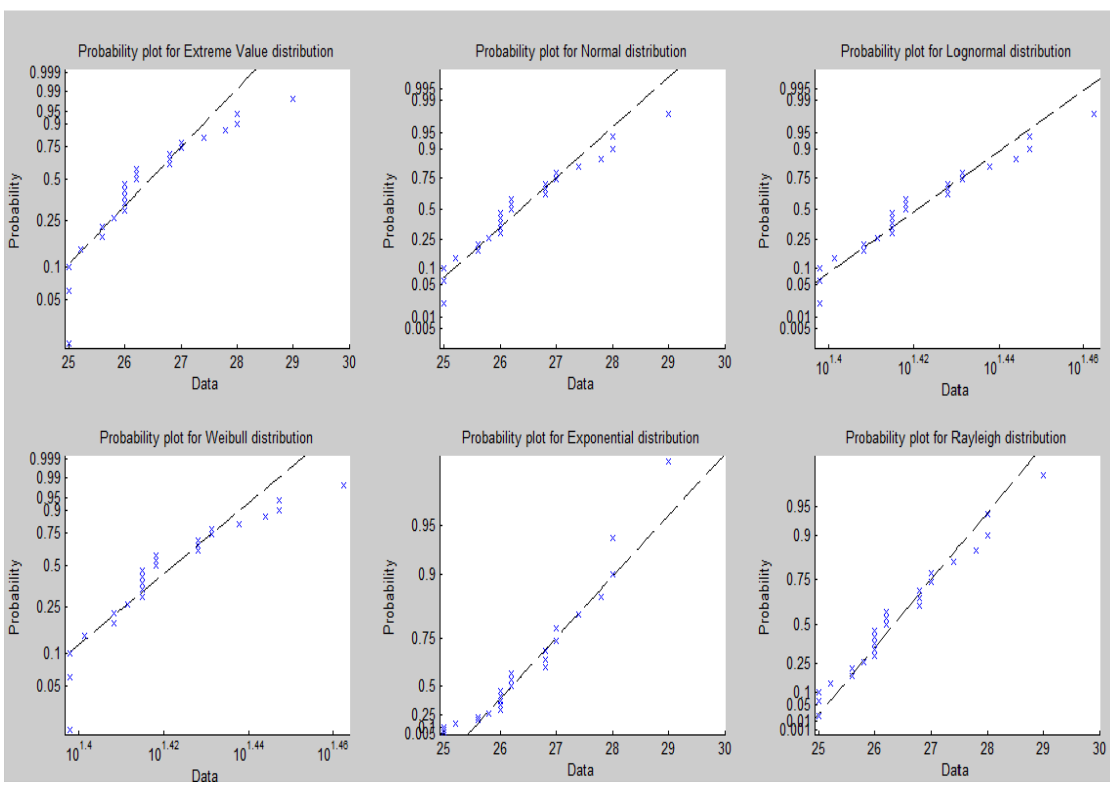


Fig. 5. Normalcy assumption validation in different scenarios

Table 1. Models' input parameters statistical description

	N	Minimum	Maximum	Mean	Std. deviation	Variance
SOIL_TEMP_NNEP	125	24.50	29.00	26.1432	1.00083	1.002
SOIL_TEMP_NEP	125	24.20	29.00	26.0952	1.01337	1.027
ATM_TEMP_NNEP	125	24.60	31.80	27.4040	1.56918	2.462
ATM_TEMP_NEP	125	24.60	31.80	27.4064	1.57120	2.469
SOIL_PH_NNEP	125	6.90	8.30	7.7272	.29276	.086
SOIL_PH_NEP	125	6.80	8.40	7.7384	.26237	.069
Valid N (listwise)	125					

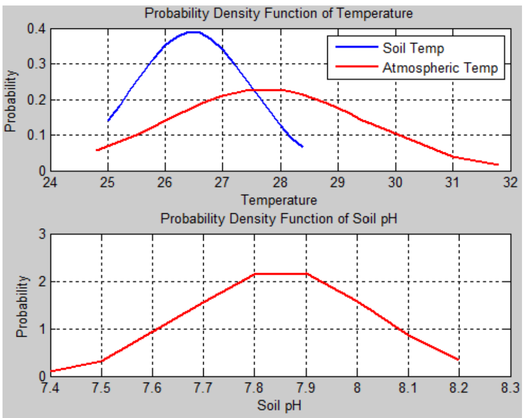


Fig. 6. Nickel electroplated sample input distribution (Location 2)

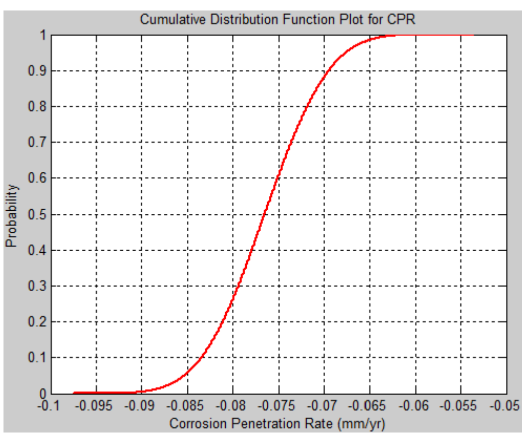


Fig. 7. CDF plot for Nickel electroplated sample. The estimated Corrosion Penetration Rate value = -7.183714e-02 mm/yr (location 2)

It is observed that the CDF plots for the Non-Nickel electroplated samples are slanting at an increasing rate which would further buttress the fact that the CPR had values spread over a wider range than those of the Nickel electroplated samples. Certain outliers however existed, for the steel samples buried in location 3 (Export Pump).For both the Nickel Electroplated sample and Non-Nickel Electroplated samples, there seems to be a deviation from the generally observed trends in the CDF plots for Corrosion Penetration Rate. This beviour can be likely attributed to a build up of a stable oxide layer on the steel surface which can slow down the rate of corrosion.

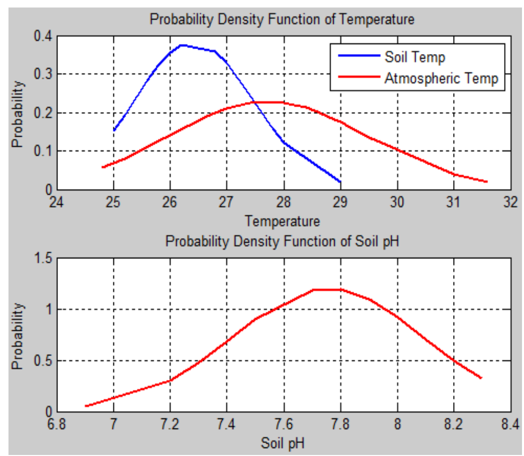


Fig. 8. Non-Nickel electroplated sample Input distribution at location 2

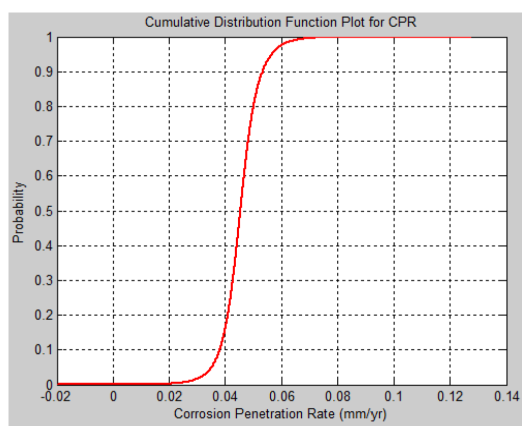


Fig. 9. CDF plot for Non-Nickel electroplated sample. The estimated Corrosion Penetration Rate value = 5.018641e-02 mm/yr at location 2

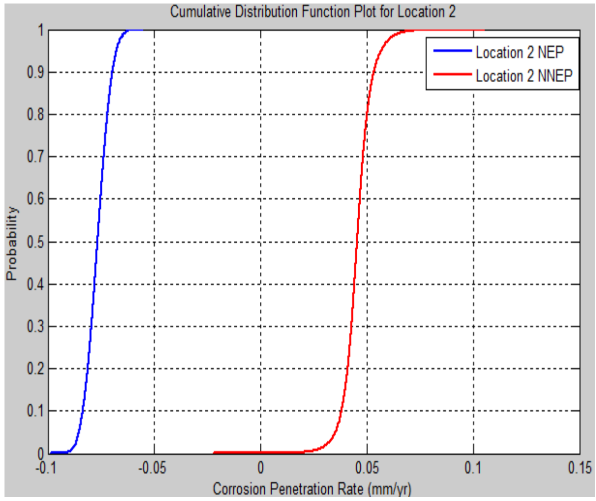


Fig. 10. Comparism of CPR for both samples in location 2

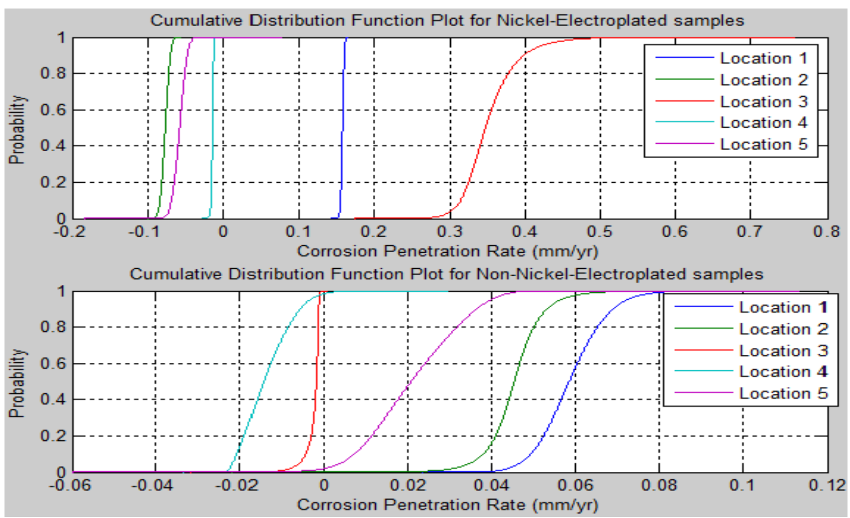


Fig. 11. Plot of CPR for all samples (NEP vs NNEP)

4. CONCLUSION

In accordance with the aim of this paper, the corrosion penetration rate of buried steel samples was modelled using MANN-MCS and corrosion data (CPR calculations) obtained via weight-loss method. These calculated CPR values and specific location properties serve as inputs for the Modified artificial neural networks which established a relationship between these input parameters and the CPR. It provides a coefficient matrix as its output. The network made use of weights of unity value and scaling factors that allowed for convergence of decimal places, ranking, crossover determination, rescaling then interpolating to regenerate the polynomial coefficients necessary for the generation of the outputs. This output is fed into the MCS as its Relating equations for the execution of its probability. Using the NACE SP0502-2010 standard [13], the 80th percentile of each plot is selected as the estimated corrosion penetration rate.

A correlation was found to exis tbetween the model results and the results obtained from experimental data. This model also validates nickel electroplating as a means of corrosion mitigation.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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