ANN and Regression Models for Estimation of Corrosion Rates of Metal Alloy Types in Oceans

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Abstract— Offshore structures are often threatened by corrosion which could result in accidents, expensive maintenance schedules or structure failure. Artificial Neural Network (ANN) and regression models were trained in this paper for estimation of corrosion rates of seven metal alloy types and variants for various depths and exposure time. Data used for training and testing the models were obtained partly from the field work carried out in this paper and mostly from three other sources of data published in the literature. Depths of data used for training range from 5 to 120 meters for shallow depths, 373m to 6780m for deep ocean depths. Trained regression and artificial neural network models have comparable performances in estimating corrosion rates on new data. Results show that the trained models can be used to estimate corrosion rates at difficult to reach locations and can help avoid accidents or structure failure and reduce expensive maintenance schedules.

Index Terms— Artificial neural network, regression model, prediction, corrosion rate, ocean, depth.

1 INTRODUCTION

PREDICTION models are very useful for monitoring environmental parameters and possible outcomes of some material given some specified circumstances. Common tools used for predictive modeling are artificial neural networks, regression models and classifiers. Artificial neural networks have great computational power, such that they can approximate or represent any logical complex function [1]; can learn from data of complex processes; and can predict and fit data with high accuracy [2]. ANN can be used for classification, regression, clustering, anomaly or fault detection [3], [4] and feature extraction. In this paper ANN and regression models were used to predict the corrosion rates of seven metal alloys types of 48 variants at water depths ranging from 5 to 6780 metres by training ANN to regress non-linear input data (metal alloy, alloy variant, days and depth) to its target data (corrosion rate).

A regression model determines the relationship amongst variables that are non-linear using regression analysis. Regression models can be developed using regression trees, a kind of decision tree. Regression trees can be simple, medium or complex, depending on the complexity of the model. Non-linear and complex relationships in data are better modeled with complex tree models than simple tree models. In this paper, medium and complex tree regression models were developed using metal alloy, alloy variant, days and depth as predictors and corrosion rate as response.

Corrosion is an undesired process and a threat to offshore structures like oil rigs, oil platforms and oil pipelines. Corrosion depends on the type of metal, alloy composition, exposure time, temperature, salinity and depth in sea or ocean water [5]. The major effect of corrosion is weight loss in corroding metal. Oil rigs and platforms are besought with danger of pitting and crevice corrosion [6]. Ultimately, these unchecked corrosions could result in deadly explosions as have been reported in some accidents, like that of the Gulf of Mexico on December 4, 2009, which resulted from a severely corroded pipeline [7]. It is therefore, essential to determine the corrosion rates of metals at certain depths in sea or ocean and hence provide guidance in designing appropriate sacrificial anodes for protection of offshore structures to prevent accidents and casualties. Several kinds of models have been used to model corrosion behaviour in pipelines such as, mechanistic models, electrochemical models using transport equation, semi-empirical models and empirical models, but these works were based on artificial aqueous medium, not on real sea or ocean water.

The major contributions of this paper are trained regression models and neural network models for estimating corrosion rates of metal alloys at various shallow and deep ocean depths; up to 7000 metres. The data used in this work is partly from the field work carried out in this paper and data gathered from three other sources. The data used for training spans measurements from the Atlantic, Pacific and Indian oceans. This paper is organized as follows: Section 1 introduces the paper while regression, classification and ANN models and their existing applications are reviewed in Section 2. The method of data collection from field work in this paper as well as gathered from other sources is described in Section 3. Section 4 describes the trained regression and ANN models in this paper as well as their training performances. Evaluation of trained models on new data is discussed in Section 5. The paper is concluded in Section 6.

2 Review of Existing Literature

Artificial Neural Networks (ANNs) have been used for prediction in Science, Engineering and Medical fields in the literature. An ANN, combined with a fuzzy inference system, was used in [8] for prediction of matching conditions for a micro-strip bandpass filter and amplifier. In [4], two wavelet ANN models, for predicting river flow based on regression analysis and support vector machines, were developed. The models could predict river flow ahead of 1 to 3 days. A wavelet ANN was proposed in [9] for predicting global solar irradiation for optimum power tracking in photovoltaic (PV) systems. In [10], an ANN was developed for prediction of colour fabrics. ANN and regression models have been used for electric energy load forecasting or profiling in [11], [12]. Shallow and deep ANN models have been developed for predicting traffic flow in [13], [14] for the purpose of designing robust intelligent traffic systems. In [15], a multi-layered ANN was used for classification and feature selection. In [16], ANN was used for wind power forecasting - a sustainable form of energy, by training the designed ANN with recorded numerical weather prediction data. ANN was used in [17] for predicting short-term wind speed in the face of uncertain input data. In [18], time-domain and optimized ANN and Support Vector Regression (SVR) models were developed for the prediction of radio frequency power for the purpose of accurate channel selection in cognitive radio technology. The training data comprised previous radio frequency power. ANN was used for prediction of the performance wastewater treatment plant in [19].

Ultimately, ANN has been used in predicting, determining and analyzing underwater corrosion rates in the literature. Partial Least Square regression method was used for analyzing and modeling metal underwater corrosion in [20]. A method for detecting the degree of corrosion in submarine oil pipelines based on chaos genetic algorithm ANN was presented. The ANN was trained with field data collected with sensors. ANN was used for assessment of corrosion in subsea pipelines in [21]. In [22], ANN was used as a predictive model for corrosion polarization curves of pipeline steel under inhibition by carboxyamide-imidazoline. An annealing ANN was employed in [23] for detecting corrosion of submarine oil pipeline. The training data were acquired from three groups of ultrasonic and flux leakage sensors. In [24], an ANN model was used to predict the corrosion rates of the internal of gas pipelines. In [25], a back-propagation ANN was developed for predicting corrosion rates of steels in sea water and analyze the effect of environmental parameters on corrosion rate. In [26], ANN was used for assessment of deteriorating reinforced concrete structures installed for thermal power plants. ANN was used for the monitoring and analysis of an initiated pitting and crevice corrosion. So far, ANN has been used for detecting and analyzing corrosion rates in sea water, but has not been combined with field data for determining or predicting corrosion rate at given depths. The objective of the regression and ANN models developed in this paper is to determine corrosion rates at any given shallow and deep ocean depth.

3 Data Collection

3.1 *Data collection from field experiments in this paper*

Parameters of Metals Used in this paper

Three metals used for the field experiment in this paper are titanium alloy (TA), high strength steel (HSS) and low carbon steel (LCS). Three metal blocks cut from these metals were used. Holes of 1cm diameter were drilled on each of the three different metal blocks using a twist drill, prior to slicing out six sheets of metals from each of the three metal blocks. The dimensions of the sliced metals were $30.7cm \times 15.5cm \times 1cm$, $38.5cm \times 15.5cm \times 1cm$ and $30.5cm \times 22.4cm \times 1cm$ for titanium alloy, high strength steel and low carbon steel, respectively. The holes were needed for fastening or suspending the metals in strings in the two ocean bays and a river. Veneer caliper was used on a bench vice to achieve accurate hole sizes in each of the eighteen sheets of metal. The metal sheets were neatly grounded using silicon carbide sand paper and were cleaned with distilled water and acetone.

The sizes, weights, alloy densities and total surface area (TSA) of the three metals are given in Table 1. Six pieces of each metal were used only.

Table 1. Initial weight and alloy densities for titanium alloy (TA), high strength steel (HSS) and low carbon steel (LCS).

Metal	Initial Weight (g)	Alloy density ($g.cm^3$)	Surface area (cm^2)
TA	1300	4.81	1037.82
HSS	1900	7.85	1295.22
LCS	2300	7.87	1465.92

Three Experiment Locations – Two Atlantic Ocean bays and a river

The three experiment locations are Atlantic Ocean location at Apapa, Victoria Island Lagos; Atlantic Ocean deep area of Nigeria Navy forward operation base (FOB) Ibaka, Akwa Ibom State; and River Niger at Onitsha, Anambra State, Nigeria. These three locations will be referred to as Apapa, Ibaka and Onitsha, respectively, in this Section of the paper. Synthetic fiber-cords were fastened onto each of the metal specimen with their identification tags.

The experiments were conducted for a total of six shallow depths in the ocean bays and river – 5m, 6m, 7m, 50m, 100m and 120m in the three locations. Six sheets of each metal types were used at each location. Two groups of metals comprising three alloy types, HSS, LCS and TA, were used in each location.

The parameters of metals utilized and measured in this paper include weight, surface area, weight loss in metal and measured environmental parameters include water temperature, salinity and pH. Water temperature and pH were measured monthly for the three water locations and depths, but cannot be contained in this paper due to lack of space and irrelevance to the goal of this paper.

Field Corrosion Rates

The corrosion rates in Table 2 were determined using the corrosion formula in equation from [27].

Table 2. Corrosion rates (CR) in mils/year of three alloys at the given locations and depths of exposure.

Location	Metal	Depth (m)	Weight loss (g)	CR (mils/yr)
Ibaka	TA	7	40	3.156
Ibaka	HSS	7	100	3.873
Ibaka	LCS	7	129	4.404
Ibaka	TA	120	30	2.367
Ibaka	HSS	120	86	3.324
Ibaka	LCS	120	99	3.390
Onitsha	TA	5	40	3.156
Onitsha	HSS	5	104	4.028
Onitsha	LCS	5	139	4.731
Onitsha	TA	50	18	1.420

Location	Metal	Depth (m)	Weight loss (g)	CR (mils/yr)
Onitsha	HSS	50	100	3.873
Onitsha	LCS	50	99	3.365
Apapa	TA	6	50	3.945
Apapa	HSS	6	100	3.873
Apapa	LCS	6	129	4.390
Apapa	TA	100	31	2.446
Apapa	HSS	100	80	3.099
Apapa	LCS	100	89	3.024

3.2 *Data Collection from published sources*

Most of the corrosion data used in this paper were gathered from three published sources with unlimited distribution, namely, experiments carried out by the Naval Civil Engineering laboratory [28] in the Pacific ocean; experiments by the National Institute of Ocean Technology in the Indian Ocean [27], and study of corrosion in water wells in [29].

In [28], a detailed and considerable study was carried out for seven major metal alloy groups and 189 variants of alloy compositions, at three ocean depths, 5m, 2370m and 6780m. The seven major metal alloy types are aluminum, copper, iron and steels, nickel, cast iron, stainless steel and titanium. These alloys had between 12 and 18 months exposure in the Pacific ocean. Majority of the training samples used in this paper were from the data from this source. Since an exhaustive list of alloy compositions were used in [28], metals or alloy compositions used in other sources were merged with the alloy names in [28].

In [27], corrosion of ferrous alloys were studied in the Indian ocean at depths of 500m, 1200m, 3500m, and 5100m, for 174 days, 189 days and 1064 days. Four kinds of alloys were used in [27] namely, mild steel, maraging steel, torsteel and ductile iron. Corrosion rates in [27], were reported in mm/year but these were converted to mils/year for use in this paper.

Five alloy types were used in [29], for studying corrosion in water wells at depth of 373m.

The total number of samples gathered from these three sources, including the field data obtained from this paper are 792. Each sample has these parameters: metal alloy type, alloy composition, number of days of exposure, depth and corrosion rate. The input parameters are all but the corrosion rate, while the output is the corrosion rate. For purposes of training reliable regression models and artificial neural networks in this paper, alloy compositions with similar response characteristics were merged to reduce redundancy and create considerable training samples for each alloy composition. The number of days of exposure were also converted to months, as significant corrosion is noticeable over months, but not overnight. Table 3 shows a short description of the parameters of the data used in the experiment in this paper.

Table 3. Short description of the parameters of the data used in the experiment

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Parameters	Number or actual values
Metal alloy types	seven
Alloy compositions	189
Regrouped alloy variants	48
Number of days of exposure	174 to 1064 days
Months of exposure	6, 10, 12, 13, 18, 20, 24, 25, 35 months
Depths	5, 6, 7, 50, 100, 120, 373, 500, 1200, 2370, 3500, 5100, 6780 metres
Corrosion rates	0.0001 to 13.2 mils / year

4 ANN AND REGRESSION MODELS

All experiments in this paper were carried out in MATLAB 2017a environment on a mac mini system with 8GB of RAM. Data was collected in excel sheets.

Parameters used to train regression and artificial neural network models are metal alloy types, regrouped alloy variants, months of exposure, depths and corrosion rates. Input parameters to the regression model and ANN are metal alloy types, regrouped alloy variants, months of exposure and depths. The response and target to the regression model and ANN is the corrosion rate parameter.

Training and testing sets of data were prepared by randomly partitioning data into training data (91% of all data) and testing data (9% of all data) for both regression and ANN models. These corresponded to 720 samples in the training set and 72 samples in the test set. This was done as the models are expected to be tested on new data not used for training to see how well they estimate corrosion rates. String or text labels in metal alloy types and variants were automatically replaced with numerical labels, corresponding to metal alloy types and alloy variants before training ANNs in this paper.

4.1 *Creating and Training of Artificial Neural Network (ANN)*

The goal of this section is to train artificial neural networks (ANN) to regress non-linear input data (metal alloy type, alloy variant, months of exposure, and depth) to given target data (corrosion rate). Three ANNs were trained, respectively, with all four input features; three input features (number of months was dropped); and two input features (months and metal group were dropped).

The training set (720 samples) were divided into 3 sets; training data (80%), validation data (10%) and testing data (10%). The ANNs were trained using the Levenberg-Marquardt backpropagation algorithm with a mean square error performance function. Levenberg-Marquardt algorithm was used because of its efficiency in non-linear function approximations and the modest data size of 720 samples. Attributes of the trained ANN models are shown in Table 4.

Table 4. Attributes of trained ANNs.

ANN number	Inputs	Number of inputs	Model type	Hidden layers
N1	Metal alloy group, alloy variant, months, depth	4	Feed forward, multi-layer	120
N2	Metal alloy group, alloy variant, depth	3		
N3	Alloy variant, depth	2		

The training, validation and test performance plots of the trained networks are shown in Figure 1, for three networks, N1, N2 and N3. The performance plots show R values, that is, regression values, for the training, validation and test. R values fall within a range of 0 and 1. A value of 1 denotes a perfect relationship amongst the variables or parameters while a value of 0 shows no relationship. Hence, the higher the regression value the better the performance. Performances in N2 and N3 improved when a parameter, number of months, was excluded from the input as shown in Figure 1 (b).

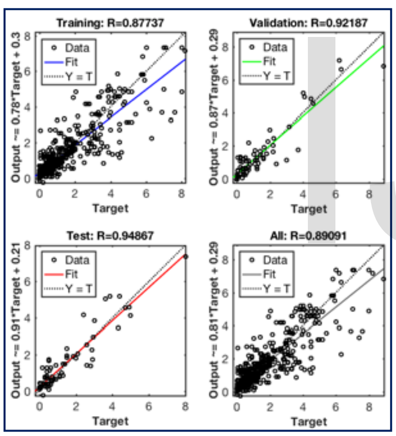
4.2 *Creating and training a regression model*

The goal of this section is to train regression models that can suitably determine the relationship amongst the non-linear parameters in the data of alloy corrosion, and hence, can give estimates of corrosion rates for metal alloy compositions, for certain months of exposure and depth in the ocean. A training set of data, 720 samples, were used to train and develop one medium and two complex tree models. A five-fold cross validation was performed on the data during training to ensure that the trees do not over fit data. Three trees model were trained with four inputs – metal alloy group, alloy variant, months and depth; three inputs (excluding months) and two inputs – alloy variant and depth. Attributes of the trained regression trees models, complex tree – M1, medium tree – M2 and complex tree – M3 are shown in Table 5.

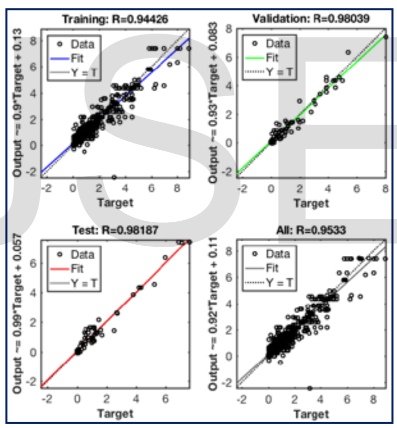
Table 5. Attributes of trained regression trees.

Model number	Inputs	Number of inputs	Model type	Minimum leaf size
M1	Metal alloy group, alloy variant, months, depth	4	Complex tree	4
M2	Metal alloy group, alloy variant, depth	3	Medium tree	12
M3	Alloy variant, depth	2	Complex tree	4

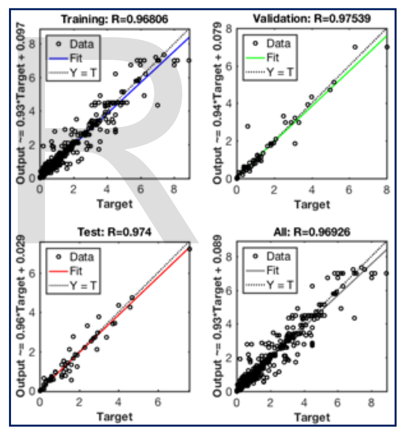
Regression plots for the trained models on are shown in Figure 2. The second model, M2, has the best regression value.



(**a**) **N1**: Network trained with 4 input features

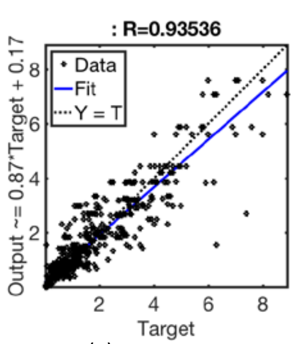


(**b**) **N2**: Trained with 3 input features

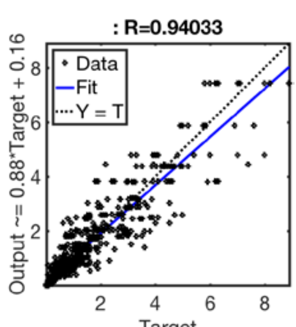


(**b**) **N3**: Trained with 2 input features

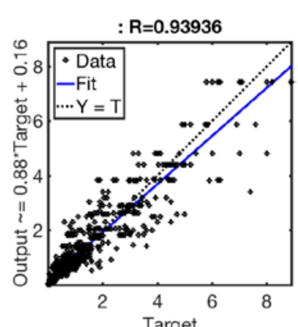
Figure 1: Training, validation and test performances for three ANNs, NI, N2 and N3, trained with four, three and two input features, respectively in (a), (b) and (c).



(**a**)



(**b**)



(**c**)

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Figure 2: Regression plots of trained models, (a) M1, (b) M2 and (c) M3.

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4 Evaluation of Trained ANNs and Regression Models on New Data: Prediction of Corrosion Rates

The trained ANNs and regression models were evaluated on new test data (72 samples), not used for training, nor validation, nor testing in this section. Values for the mean square error (MSE) for the ANNs and trained regression models when evaluated on new data are shown in Table 6. The less the MSE value the better the performance. MSE values in Table 6 show that trained ANN, N2, with MSE = 0.6962, is better than M2 with MSE = 0.7523, while regression models M1 and M3 are better than N1 and N3 respectively. The overall best model is N2 from the least MSE value.

Regression plots for the evaluation of trained ANNs (N1, N2 and N3) on new data are shown in Figure 3 (a), (b) and (c), while regression plots for the trained regression models (M1, M2 and M3) on new data are shown in Figure 3 (d), (e) and (f). Performance of N2 with R = 0.89808, is better than M2, with R = 0.88584, whereas performances of M1 and M2 are better than N1 and N3 respectively. This shows that ANN trained with three features is able to estimate corrosion rates better than a regression model trained with three input features. However, regression models, M1 and M3, trained with four and two input features, respectively, are better in estimating corrosion rates, compared to neural network models, N1 and N3. Trained artificial neural network, N2, has the best regression value of 0.89803.

Table 6. Mean square error (MSE) for the three regression models and three ANNs when evaluated on new data.

R-Model number	MSE	ANN number	MSE
M1	0.8057	N1	1.2142
M2	0.7523	N2	0.6962
M3	0.7057	N3	0.8136

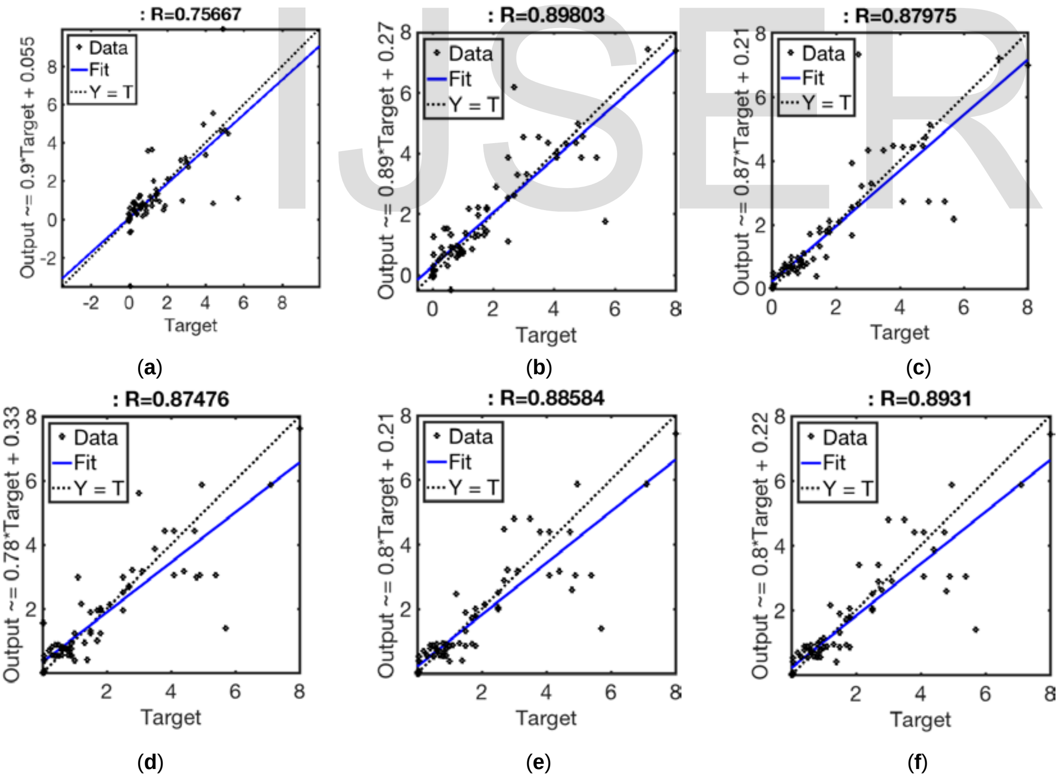

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Figure 3: Regression plots for the evaluation of trained ANN models, N1, N2, and N3, and regression models, M1, M2 and M3, on new data. (a). N1 (b). N2. (c). N3. (d). M1. (e). M2. (f). M3.

5 Conclusion

In this paper, ANN and regression models were developed for estimation of corrosion rates of seven metal alloy types with 48 variants for shallow and deep ocean depths. The models were trained with data ranging from 5m to 6780 metres. Trained regression model and artificial neural network have comparable performances for estimation corrosion rates form the results obtained by evaluating the models on new data. These models would be useful for estimating corrosion rates especially in difficult to reach locations, such as, ocean depths beyond 3000 metres, and hence provide timely information for appropriate design and maintenance of offshore structures.

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