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Determination and prediction of corrosion integrity on RV discovery via Non-Destructive Test (NDT) and Artificial Neural Network (ANN)

Mohammad Fakhratul Ridwan Zulkifli[1,*],Mohamad Ashraf Bin Adlin[1], Suriani Mat Jusoh[1], Samsuri Abdullah[1], Mohd Sabri Bin Mohd Ghazali[1,2] and Wan Mohd Norsani Wan Nik[1]

[1]Marine Materials Research Group, Faculty of Ocean Engineering Technology and Informatics, Universiti Malaysia Terengganu, 21030 Kuala Nerus, Terengganu, Malaysia
[2]Faculty of Marine Science and Environmental, Universiti Malaysia Terengganu, 21030 Kuala Nerus, Terengganu, Malaysia

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☒*Corresponding author:
Dr. Mohammad Fakhratul Ridwan Zulkifli
Faculty of Ocean Engineering Technology and Informatics, Universiti Malaysia Terengganu, 21030 Kuala Nerus, Terengganu, Malaysia
Email: fakhratulz@umt.edu.my

Abstract

Marine environment is a harsh and severe environment for a metal structure like vessel, oil rigs and port infrastructure. A regular survey or monitoring is needed to reduce a structure failure due to the corrosion. To be seaworthy, a vessel should undergo a regular survey under specified timeframe. This survey is time consuming and costly. An alternative approach is required to predict the structural integrity of a vessel. Artificial Neural Network is one of the current methods that can be used to predict the deterioration rate of a structure. Corrosion integrity of RV-Discovery was determined via plate thickness measurement, coating thickness measurement and potential measurement. The data obtained from these measurements were used in an artificial neural network to predict the deterioration rate. The results indicate that the plate and coating thickness reduction percentage is within minimal range while the average potential changes show that the structure is in passivation state. It implies that the structural integrity is in a good state with no or minimal maintenance required. The prediction of deterioration rate also shows that the Scaled Conjugate Gradient (SCG) training algorithm was able to predict with over 95% of confidence and low mean square error.

1. INTRODUCTION

Seawater contains a significant concentration of dissolved salts and is very corrosive to steel, infrastructure, and assets in or near marine environments are particularly susceptible to corrosion (Babu *et* al., 2014). The corrosion in marine environment will deteriorate the thickness of the structure and eventually triggered other kind of failure modes of the structure as occurred on a tanker known as Prestige which exhibits an acute impact of structural failure due to the corrosion (Zima *et al.,* 2022, Woloszyk *et al*., 2018).

Coating is always opted as a corrosion protection for the structures in marine environments. Application of coating will improve the service life of the structure (Sharma and Goyal, 2022). However, due to the harsh marine environment coupled with several mechanisms, the coating will degrade over time and consequently initiate the corrosion defects (Tator and Tator, 2015). Inspection of the structure is crucial to detect any structural or coating failure prior to repair and maintenance (IACS 2006). According to the guidelines of Classification Societies, the regular survey is required where the thickness of the metal structure will be measured using an ultrasonic thickness gauge due to its portability, ease of use and reliability.

Research Vessel Discovery or RV-Discovery are one of the oceanographic research vessels operated in Malaysia. This vessel is owned and operated by Universiti Malaysia Terengganu to carry out studies and research in the coastal and marine areas in Malaysia. In line with UMT's slogan "Ocean of Discoveries, for Global Sustainability", RV-Discovery is considered a history to UMT of being able to carry out research and marine science at once, placing UMT as the premier institution in the country in its field.

To ensure the RV-Discovery to operate safely and efficiently, she must undergo the inspection process. In this study, corrosion integrity of RV-Discovery was studied through plate thickness measurement, coating thickness measurement and potential measurement. The collected data then were used in the Artificial Neural Network tool to model the deterioration rate. ANN is one of the most popular techniques for exploration of complex phenomena (Mahjani *et al*, 2004). ANN has emerged as a powerful tool

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for the prediction of deterioration rate of metal that is exposed with the period (Alam, 2016)

2. MATERIALS AND METHODS

Data collection was carried out onboard RV Discovery when the vessel was anchored at the jetty of Pulau Duyung Kuala Terengganu. The ship deck has been divided into three different regions, known as A, B and C as shown in Figure 1. This area was selected as it provides easy accessibility for data collection and exposed to the splash of seawater during voyages. The data of plate thickness, coating thickness and potential were collected from five points in each region. The data collection uses a non-destructive test method, such as Ultrasonic Thickness Gauge, Ultrasonic Coating Thickness Gauge and Digital volt ohmmeter (DVOM). Three readings were taken in each point and the average reading was calculated. The data was collected three times in every two weeks where the data from the first two weeks were selected as baseline data.

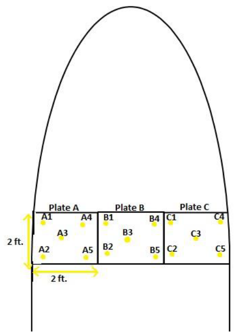

Figure 1: Frame is measured at 5 different point within 4 square feet (2ft x 2ft).

Deterioration rate was determined through the changes of plate thickness, coating thickness and potential/voltage changes on the hull surface. The percentage of plate thickness reduction and coating thickness reduction were calculated based on the following equations:

$$\%\ after\ 2\ weeks = \left[\frac{(w2a1 - w4a1)}{w2a1}\right] \times 100 \quad (1)$$

$$\%\ after\ 4\ weeks = \left[\frac{(w2a1 - w6a1)}{w2a1}\right] \times 100 \quad (2)$$

Where w is week, 2 refers to the week number, a refers to region and 1 refers to tested point.

The data from three NDT methods were used as an input in ANN. There are 135 data used for prediction study. The database was randomly divided into three groups with 70% for training, 15% for testing and 15% for validation. Plate thickness, coating thickness and potential of plate were considered as input variables in the artificial neural network model while deterioration rate was selected as the output. The architecture of the ANN is shown in Figure 2. Since the input variables in the dataset have different magnitude, a normalization of them is required. The normalization was conducted within the range between 0.1 and 0.9 to scale the dataset into a smaller range and to avoid the dilution in effectiveness of the selected algorithm using the following equation:

$$\emptyset n = 0.8 * \left[\emptyset - \frac{(\emptyset)}{(\emptyset) - (\emptyset)}\right] + 0.1 \quad (3)$$

Where $\emptyset n$ is the normalized input variable, $\emptyset$ is the data, min is the minimum value in the dataset and max is the maximum value in the dataset.

Scaled Conjugate Gradient (SCG) was selected as a supervised training algorithm. The scaled conjugate gradient algorithm was introduced by Møller (1993). It is based on conjugate directions, but it does not employ a search-line technique at each iteration. The general idea of SCG is, it estimates the step size of conjugated gradient (CG) with a non-symmetric approximation using comparison parameters, Δk. The closer this value to 1, the better approximation will be obtained. The training of the algorithm will stop when the following conditions occurs:

- The maximum number of epochs (repetitions) is reached.
- The maximum amount of time is exceeded.
- Performance is minimized to the goal.
- The performance gradient falls below min_grad.
- Validation performance (validation error) has increased more than max_fail times since the last time it decreased (when using validation).

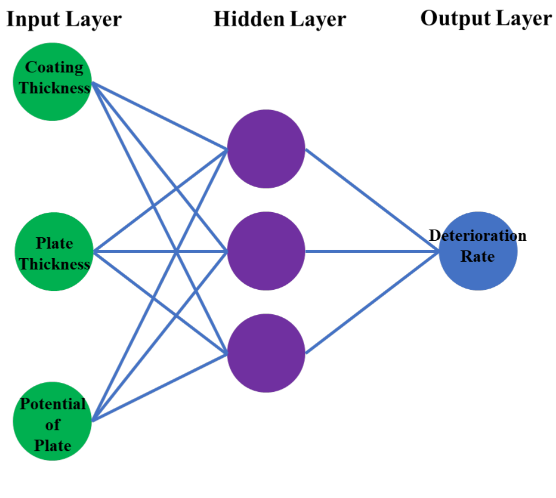

Figure 2: Neural network architecture.

3. RESULT AND DISCUSSION

3.1 Plate Thickness Reduction

Ultrasonic thickness test which is non-destructive techniques is a good way to measure the thickness of plate on RV-Discovery at several point areas. In this scope of study, the ultrasonic thickness test was done at three different frame areas, which is area A, B and C on RV-Discovery. So, there are different percentage reduction results due to different thickness on frame on RV-Discovery. Figure 3 shows the comparison of the test region within 4 weeks due to the plate thickness reduction.

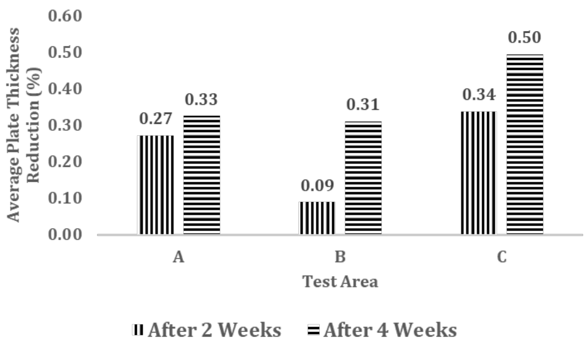

Figure 3: Average of plate thickness reduction percentage.

As seen, the plate thickness reduction percentage in area A, B and C has a value below 1.0% indicating that the plate is in a good condition. It is found that the average plate thickness reduction is higher at region A and C which could be due to the continuous exposure to the splash seawater. As the exposure period increases, the percentage of plate thickness reduction also increases. However, the differences of the plate thickness reduction after 2 and 4 weeks at area B is higher in comparison to area A and C. This could be due to surface deformation on the coating and metal surface. In overall, the average plate thickness reduction percentage of all regions is considerably low indicating that the plate did not have an obvious change and the failure remained unchanged (Qiu *et al.*, 2022). The similar trend was also observed in an experimental procedure conducted by Nakai *et al* (2004) to study the effect of pitting corrosion of bulk carriers where the average thickness reduction was found to be around 2.72 – 0.00 mm (2.72 – 0 %).

3.2 Coating Thickness Reduction

Using a coating thickness test, the thickness of coatings can be measured to ensure that they achieve the IMO Performance Standards for Protective Coatings (PSPC) (Baek, 2008). Coatings on metal structures need to be at the correct thickness to achieve the proper protection because corrosion usually starts in areas of coating damage, and areas where the coating can be of poor quality e.g., weld seams, edges, and notches, etc (Amirafshari *et al.*, 2018). Readings of coating thickness onboard RV-Discovery are taken at three different region which are A, B and C, to ensure that sufficient coating thickness overall has been applied. Figure 4 shows the comparisons of the test area within 4 weeks due to the coating thickness reduction.

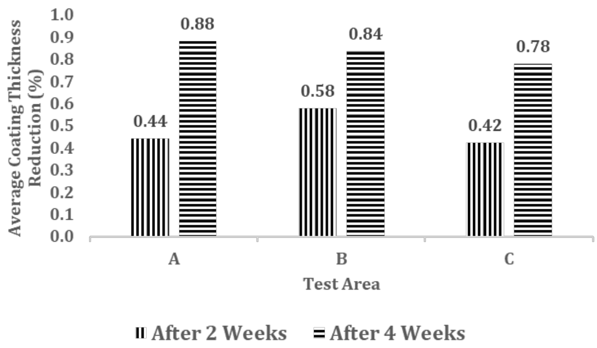

Figure 4: Average of coating thickness reduction percentage.

The average value of coating thickness reduction increases as the period of the exposure increases. A prolonged exposure to the marine environment would slowly deteriorate the coating. The average percentage of coating thickness reduction is found to be below 1%.

Region B exhibits greater coating reduction, and the visual inspection reveals that there are blisters and coating deformation at this area as seen in Figure 5. Blisters either originate from ionic contamination on the substrate, prior to coating, or are due to soluble material leaching out from the coating itself and migrating to the interface with the substrate. Driven by osmosis, water will always migrate through the film and when the osmotic pressure within the blister balances the coating adhesion around its circumference, the blister ceases to grow (Hamburg and Morgans, 1979).

Figure 5: Blister rash on coating of RV-Discovery.

3.3 Changes in Potential

Every metal takes up a specific electrochemical potential when immersed in a conducting liquid. This potential is called the half-cell potential as it can only be measured by comparing it to another known reference potential produced by a reference electrode. Common reference electrodes are the Saturated Calomel Electrode (SCE), silver/silver chloride and copper/copper sulfate reference electrodes (James *et al.*, 1998). The potential that a metal takes up in a solution can determine if and how fast it will corrode. Figure 6 shows the comparisons of the test region within 4 weeks due to the changes of potential.

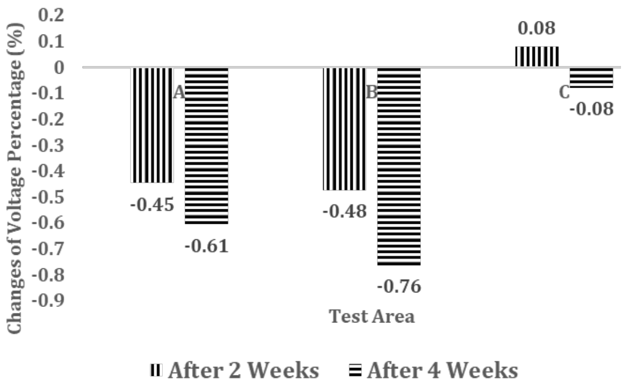

Figure 6: Average of potential changes percentage.

The potential of the coating surface shows two distinctive movements of the potential polarity. The negative change in potential percentage indicates that the potential is moving towards the positive potential region while the positive change implies that the potential is moving towards the negative potential region. The changes of potential towards the positive potential region shows that the coating surface is under passivation region where the anodic site of the metal is hindered from undergoing corrosion process (Bennedeti *et al*., 2016, Zulkifli *et al*., 2017). At this point, the anodic reaction is suppressed which reduces the metal dissolution and increases the hydrogen evolution process. The accumulation of more hydrogen in the process helps to minimize the oxidizing species and avoid the formation of corrosive environments (Choudhry *et al.,* 2014).

3.4 Artificial Neural Network (ANN)

ANN study was carried out using Scaled Conjugate Gradient (SCG) as a training algorithm with six neurons in the hidden layer and according to the input and output variables of the problem. Table 1 summarizes the main result of neural network training and neuron number 3 is the best fitting by SCG.

Table 1: Regression and mean square error (MSE) of trained dataset with six neurons in the hidden layer.

Neuron	Regression, R	Mean Square Error, MSE
1	0.99540	$3.10x10^{-4}$
2	0.99878	$2.39x10^{-4}$
3	0.99893	$2.16x10^{-4}$
4	0.99127	$1.26x10^{-3}$
5	0.99876	$2.55x10^{-3}$
6	0.99031	$1.82x10^{-3}$

Neuron number 3 shows the best R and MSE value of 0.99893 and 2.16 x 10^{-4} respectively. Figure 7 represents the regression plot for training, testing and validation of the dataset. Regression R values measure the correlation between outputs and targets. The R values for training, validation and test are 0.9991, 0.99884 and 0.99851 respectively, yielding an overall R-value of 0.99893. This clearly indicates the ANN has a 99% confidence in predicting the deterioration rate of RV-Discovery.

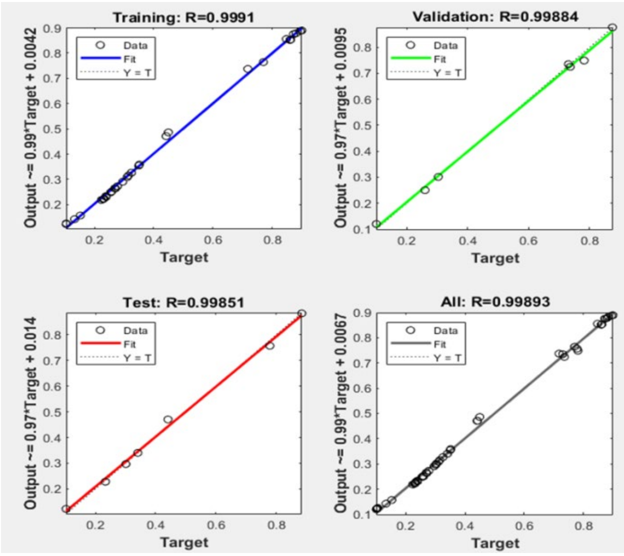

Figure 7: Regression plot for the training, validation, and testing dataset for prediction of deterioration rate.

The accuracy of the network was evaluated by the mean squared error (MSE) and the regression (R) is a measure of how well the regression line represents the actual data set. It can vary from 0 to 1. An R value close to 1 indicates that the ANN model perfectly predicts the output. The SCG training algorithm uses unconventional methods to search for the weight of each path which produces faster convergence (Møller, 1993). The gradient descent method uses reference points plotted to find the lowest point in the model and uses more epochs to get the best results (bin Zulkifli *et al*., 2021, al Bataineh and Kaur, 2018). Hence it is selected as a training algorithm in this study.

4. CONCLUSION

In conclusion the research has successfully determined the corrosion integrity of RV-Discovery and predicted deterioration rate based on the dataset obtained. It was found that the plate and coating thickness reduction percentage show a minor change within the tested period indicating that the structure integrity is still in a good state and no repair or maintenance required. However, a close monitoring of critical areas is required to ensure that no severe corrosion will happen. A simulated data was developed through a non-linear regression model with regression value of 0.99893 and a mean square error, MSE, of $2.16x10^{-4}$ in the validation stage. The model meets the requirements of the intercept statistical test with over 95% confidence. The linear model obtained is useful in predicting the deterioration rate of RV Discovery plate given that the input data is provided.

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