Identifying corrosion of carbon steel buried in iron ore and coal cargoes based on recurrence quantification analysis of electrochemical noise

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A B S T R A C T

The effect of bulk cargo materials – iron ore and coal – on the corrosion of cargo hulls in carriers was investigated using electrochemical noise. Two reference corrosion systems were set up with the steel samples in contact with moist silica sand and immersed in NaCl solution, which generated localised corrosion and general corrosion, respectively. The electrochemical noise was measured and recurrence quantification analysis was used to extract feature variables. A random forest model using these feature variables as predictors was able to discriminate between the two reference corrosion systems. This model was successfully applied to the assessment of carbon steel corrosion in iron ore and coal. The results predicted by the model were in agreement with visual and microscopic observations of the relevant corroded steel samples. This work provides a novel analytical approach to future on-line monitoring of carrier structures in contact with bulk cargoes.

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1. Introduction

Steel carriers are commonly used for transportation of cargoes, such as coal and iron ore [1,2]. Corrosion has been identified as one of the major causes of ship structural failures [3–5]. Fortunately, with adequate maintenance and proper protection of the steel structures, the impact of corrosion could be controlled. However, field observations revealed that the maintenance practices were not always sufficient and some areas, such as the lower parts of the bulk coal and iron ore carriers, might not be suitable for the implementation of protection measures [3]. Therefore, an enhanced corrosion monitoring program is called for to guide efficient inspections and timely maintenance plans.

Corrosion can occur in different forms at different positions of the cargo hold of the bulk carrier. The overall thickness of the steel structure could be considerably reduced due to continuous general corrosion. In comparison, localized corrosion may result in little mass loss, but could lead to decrease of the strength of the steel structure and cause crack or penetration of the steel structure without pre-warning [6,7]. Real-time monitoring of the corrosion processes could increase the chance of capturing the fault conditions of the steel structures and reduce unnecessary inspections, thereby decreasing the maintenance cost.

Previous experimental studies on corrosion of steels by bulk cargoes, like coal and iron ore, mainly focused on the factors that influenced general corrosion rates, including particle size, quantity of moisture, pH level as well as chloride and sulphate concentrations in the water phase of the ores [8–10]. To date, little attention has been paid to the real-time monitoring of the corrosion process at steels in contact with bulk cargoes and no studies have been carried out on the identification of different corrosion types.

There are a number of corrosion monitoring techniques that are frequently used in industries to assist the development and implementation of inspection and maintenance programs, such as electrical resistance (ER), linear polarisation resistance (LPR) and electrochemical impedance spectroscopy (EIS). Although these techniques could provide near real-time corrosion rate related to general corrosion process, they are not particularly useful in detecting localised corrosion events [11,12].

It is widely recognized that electrochemical noise (EN) generated from corrosion processes bears valuable information regarding the underlying forms of corrosion [13–16]. Localised corrosion events can be revealed by indicators derived from the collected EN
signals with appropriate analytical approaches. Over the past few decades, a variety of parameters derived from the EN data have been proposed for corrosion monitoring and corrosion type identification, e.g. localisation index or pitting factor [17], characteristic charge and frequency [18], roll-off slope of the power spectral density plot [19], correlation dimension [20], energy distribution plot (EDP) [21], etc. Nevertheless, contradictory results have been observed and no agreement has been reached as to the optimal measures.

More recently, recurrence quantification analysis (RQA) has been employed to interpret EN data [22–24]. It was demonstrated that feature variables extracted from EN data by use of RQA were capable of capturing the characteristics of different types of corrosion processes. Furthermore, in our recent studies [25–27], the combination of RQA and advanced machine learning methods was shown to be capable of distinguishing localised corrosion from general corrosion in-situ.

Specifically, the EN data segment was first converted to a so-called recurrence plot, from which twelve variables were then extracted. A recurrence plot is in essence a graphical representation of a square matrix, which is commonly expressed as \(R_{ij} = H(\varepsilon - ||x_i - x_j||)\). In our studies, \(R_{ij}\) represents the \((i, j)\)th point in the recurrence plot. \(\varepsilon\) is a predefined threshold value, \(x_i\) and \(x_j\) are the measured EN values at times \(i\) and \(j\), and \(|| \cdot ||\) refers to the Euclidean distance between this pair of data points. \(H(\cdot)\) represents the Heaviside function, which gives the value of one, if the distance between \(x_i\) and \(x_j\) falls within the threshold. Otherwise, it is zero.

The quantification of the recurrence plots is termed as recurrence quantification analysis (RQA), by which various feature variables can be derived.

In previous investigations [25,26], twelve variables extracted by RQA method, as shown in Table 1, were used as predictors of a random forest (RF) model to distinguish between uniform, pitting and passivation processes of carbon steel in NaCl solution, NaHCO\(_3\) + NaCl solution, and NaHCO\(_3\) solution respectively. Furthermore, the RF model was capable of identifying pitting corrosion of carbon steel beneath sand deposit and general corrosion in CO\(_2\)-saturated brine [27].

The present study is an extended application of the methodologies and the data analytical procedures proposed earlier [25–27]. The objective is to identify the types of corrosion process that take place at carbon steel exposed to the two bulk cargoes investigated. Two other corrosive systems, which are expected to result in general and localized corrosion, are used to obtain electrochemical noise data for development of the random forest model. Specifically, carbon steel immersed in NaCl solution will be used for general corrosion assessment, and silica sand moist with NaCl solution is used for localized corrosion assessment. Deposits of silica sand at carbon steel have been previously shown to cause pitting [28]. A random forest model will be developed based on recurrence quantification analysis of the EN data generated from these two reference corrosion systems to discriminate between the two types of corrosion. Once established, this model will be applied to identify the corrosion types of specimens buried in iron ore and coal cargoes on the basis of associated EN recordings. This could be accomplished in real time, without having to take the specimens out. It is expected that this work could offer an additional analytical method for corrosion monitoring of bulk cargo carriers.

### 2. Experimental work

#### 2.1. Materials

Carbon steel specimens (grade 1030) with chemical compositions of (wt.%): C (0.37), Si (0.282), Mn (0.80), P (0.012), S (0.001), Cr (0.089), Ni (0.012), Mo (0.004), Sn (0.004), Al (0.01), and Fe (balance) were used in this study. Two rectangular specimens with the same dimensions of 1.5 cm × 1.4 cm × 0.5 cm were soldered with a conducting wire for electrical connection and then electrocoated using Powercron 6000CX. Afterwards, the two specimens were mounted together in epoxy resin (Epofix), leaving approximately 2 cm\(^2\) for each specimen as a working surface. This assembly, named as EN electrode, was used as working electrode in the electrochemical noise tests. Prior to EN tests, the electrode was ground on silicon carbide paper up to 240 grit, followed by rinsing with ultrapure water and ethanol and finally drying with nitrogen.

### Table 1 Recurrence quantification variables.

<table>
<thead>
<tr>
<th>Number</th>
<th>RQA variable</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Recurrence rate</td>
<td>(RR = \frac{1}{RT} \sum_{i=1}^{RT} R_{ij}(\varepsilon))</td>
</tr>
<tr>
<td>2</td>
<td>Determinism</td>
<td>(DET = \frac{1}{RT} \sum_{i=1}^{RT} l_{max} - 2P(l) - \text{Histogram of the diagonal lines* of length } l)</td>
</tr>
<tr>
<td>3</td>
<td>Averaged diagonal length</td>
<td>(L_{\text{mean}} = \frac{1}{N_{\text{max}}} \sum_{i=1}^{N_{\text{max}}} P(l))</td>
</tr>
<tr>
<td>4</td>
<td>Length of longest diagonal line</td>
<td>(L_{\text{max}} = \max {l_{max} - 1, 2, \ldots N_{\text{v}}} )</td>
</tr>
<tr>
<td>5</td>
<td>Entropy of diagonal length (ENTR1)</td>
<td>(\text{ENTR1} = - \sum_{l_{\text{v}}} \ln p(l) \ln(p(l)) - \text{Probability distribution of diagonal lines.})</td>
</tr>
<tr>
<td>6</td>
<td>Laminarity</td>
<td>(\text{LAM} = \frac{1}{N_{\text{v}}} \sum_{l_{\text{v}}} p(l))</td>
</tr>
<tr>
<td>7</td>
<td>Trapping time</td>
<td>(TT = \frac{1}{N_{\text{max}}} \sum_{l_{\text{max}}} p(l))</td>
</tr>
<tr>
<td>8</td>
<td>Length of longest vertical line</td>
<td>(V_{\text{max}} = \max {l_{\text{v}} - 1, 2, \ldots N_{\text{v}}} )</td>
</tr>
<tr>
<td>9</td>
<td>Recurrence times of 1st type</td>
<td>(\text{RT1}(i) = t_{i+1} - t_{i+1} - 1, 2, \ldots )</td>
</tr>
<tr>
<td>10</td>
<td>Recurrence times of 2nd type</td>
<td>(\text{RT2}(i) = t_{i+1} - t_{i+1} - 1, 2, \ldots )</td>
</tr>
<tr>
<td>11</td>
<td>Entropy of recurrence period density (ENTR2)</td>
<td>(\text{ENTR2} = \frac{1}{N_{\text{max}}} \sum_{l_{\text{max}}} P(l) \ln P(l) = R(l)/N_{\text{max}} - \ln R(l))</td>
</tr>
<tr>
<td>12</td>
<td>Transitivity</td>
<td>(\text{TRANS} = \frac{\sum_{i=1}^{N_{\text{v}}} R_{ij} R_{jk} R_{ki}}{\sum_{i=1}^{N_{\text{v}}} R_{ij} R_{ik}})</td>
</tr>
</tbody>
</table>
Corrosiveness of two different bulk cargo materials, iron ore and coal, was assessed in separate tests. The moisture contents of the as-received iron ore and coal materials were 8.6 wt% and 5.8 wt%, respectively. In addition, test with 0.04 wt% NaCl solution (no solid material tested), and one with silica sand moistened with NaCl (0.04 wt%) were carried out as reference systems. The concentration of NaCl of 0.04 wt% in the test solution was used to match the conductivity of the leached solutions from iron ore and coal materials. The conductivity was determined using 500 g of iron ore that was immersed in 500 ml ultrapure water at room temperature. The conductivity of the supernatant after 24 h of immersion was 372 μS/cm. Similarly, the conductivity of the supernatant from coal was 654 μS/cm. Therefore, 0.04 wt% NaCl solution equivalent to a conductivity value of 625 μS/cm was chosen. The moist silica sand used in the electrochemical test was prepared using silica sand (Sigma Aldrich) with average particle size of 303 μm mixed with NaCl solution. The sand amount of 1 kg was mixed thoroughly with 10 ml of the NaCl solution (0.04 wt%) for the test.

2.2. Electrochemical noise measurement

The EN test with NaCl solution was conducted in at ambient temperature (22 ± 1 °C). The EN electrodes was placed horizontally in the cell with the working surface facing upwards and then 50 ml of the test solution was added. A double junction Ag/AgCl electrode (Orion) used as reference electrode was placed in a Luggin capillary filled with 1.5 wt% agar and 3.5 wt% KCl mixture. The Luggin capillary was inserted in the test cell with the tip in close proximity to the EN electrode. The test cell was aerated throughout the test. For sand and iron ore, the test was conducted in a 1 L glass vessel with glass lid at ambient temperature. The cell was filled with the test materials to the vessel neck. The solids were added to the cell by layering the tested material. The thickness of the first layer was about 40 mm. The bottom layer was compacted using a ’D’ type Proctor/Fagerberg hammer specific for this material compaction. Then the carbon steel electrode was placed on top of this layer with the working surface facing upwards. In addition, the Luggin capillary was inserted into the cell and its tip was kept as close as possible to the working surface of the electrode by using an iron stand to maintain its position. Afterwards, the second layer of the solids with a thickness of 15 mm was added and gently compacted with fingers. Similarly, another 5 layers with a thickness about 15 mm for each was added in sequence. The total height of the solids in the cell was 130 mm. Finally, the cell was covered with the glass lid fitted with Luggin capillary and the conducting wires of the EN electrode. All the unused openings were closed with fittings. For the test with coal cargo, the cell setup was similar except that the cell lid was additionally equipped with a condenser and the test cell was placed in a water bath to maintain constant temperature of 55 ± 1 °C. This temperature is generally considered the maximum temperature simulating real cargo shipping conditions and is also prescribed in classification procedures of corrosive substances (in liquids) [29]. The cell was carefully sealed with Parafilm to ensure no loss of moisture during the test.

A Gamry potentiostat Reference 600 operating in the zero resistance ammeter (ZRA) mode using ESA410 data acquisition software was used in this study. The current flowing between the two steel specimens and the potential between the coupled WE’s and the reference electrode were recorded simultaneously. The data sampling rate was 2 Hz since the preliminary work showed that the sampling rate of 2 Hz allowed for detection of pitting events. All the tests were conducted for 7 days, following the test methods recommended by the United Nations on the classification of corrosive substances for transportation [29]. An open source Matlab toolbox, Cross Recurrence Plot Toolbox, developed by Marwan et al. [30] was used for the recurrence quantification analysis of EN data.

2.3. Surface profile analysis

After completing a test, the electrodes retrieved from the test cells, were flushed with ultrapure water and ethanol to remove any residual ore cargo material, as well as loose corrosion products. To further remove adherent products, the sensors were treated repeatedly with Clarke’s solution according to ASTM standard G1 [31] in an ultrasonic water bath. Afterwards, the sensors were dried with nitrogen gas and stored in a vacuum desiccator for further analysis. The 3D profiles of the specimens were examined using a 3D profilometer (Alicona Instruments, IFM G4).

3. Results and discussion

3.1. Corrosion of carbon steel in NaCl solution and in moist silica sand

3.1.1. Post-immersion surface profilometry analysis

For the specimens immersed in NaCl solution (0.04 wt%), it was expected that the specimens would undergo minor general corrosion. Indeed, as indicated in Fig. 1(a1), the specimen exhibited general corrosion and no localised corrosion was observed at the surface. The image (Fig. 1(a2)) with a larger magnification further confirmed the corrosion morphology of the specimen. By contrast, the specimens buried in silica sand were subjected to localised corrosion, as shown in Fig. 1(b1). The pit depths were in the range of 20–120 μm. Fig. 1(b2) shows a magnified area with a large pit. The deepest point marked by an arrow has a depth of 113 μm.

3.1.2. Development of the classification model for corrosion type identification

To distinguish between the general corrosion and localised corrosion generated by the reference tests, the raw electrochemical current data were first divided into short contiguous segments. Each of the segments contained 1024 data points, equivalent to a time frame of 512 s. After removing the linear trend of each current segment, recurrence plots were generated by applying a threshold to the distance matrices derived from each segment. The threshold (ε) has a significant influence on the appearance of the recurrence plots and by extension the quantification variables subsequently generated from these plots. If ε is too small, there may not be enough recurrence points or recurrence structures. On the other hand, if ε is too large, almost every point would be recurrence point, which may lead to many spurious artefacts [30]. Several options for the selection of ε have been proposed in literature.

For example, ε can be chosen according to the phase space diameter [32,33], recurrence rate [34], standard deviation of the observational noise [35], and standard deviation of the measured time series [36]. Nevertheless, selection of the optimal criterion is strongly dependent on the system under study [30]. In this investigation, the threshold value was selected following previous studies [25–27], i.e. based on the standard deviation (σ) of the measured electrochemical current time series.

In the preliminary work, several threshold values (0.02σ, 0.2σ and 0.5σ) were examined and 0.5σ was selected since the developed RF model could best differentiate between the two types of corrosion. Fig. 2 shows two examples of detrended current segments and associated recurrence plots using 0.5σ as the threshold. As can be seen, the pattern of the RP obtained from uniform corrosion process differs from that associated with localised corrosion. It can be expected that the quantification variables extracted from these RPs would have different values, by which
localised corrosion and uniform corrosion processes can be discriminated.

Discrimination between general corrosion and localised corrosion was realised by a random forest (RF) model trained with recurrence quantification variables (denoted as RQA variables) extracted from the recurrence plots. The procedures are briefly outlined below. Details about the calculations and concepts related to the RF model can be obtained from previous studies by Hou et al. [25–27].

a. Twelve RQA variables were extracted from each one of the current noise segments.

b. Row vectors comprising the RQA variables were labelled with ‘A’ and ‘B’ depending on the type of corrosion from which the current signals were recorded. As a result, 2349 row vectors with labels were obtained in total.

c. From the 2349 labelled vectors, 70% were randomly selected as training data to build the RF model and the remaining 30% constituted a test dataset for validation purpose.

d. The trained RF model was evaluated by the so-called ‘out-of-bag’ (OOB) errors approach.

e. The test datasets were submitted to the RF model for classification. Finally, the misclassification error, defined as the ratio of incorrectly classified data to the total number of test data, was calculated.

Fig. 3 shows the OOB errors of the developed RF model. The results from five independent runs suggest that when the number of trees contained in the ensemble exceeded 40, the RF model based on the current data exhibited low classification errors for the discrimination between general corrosion and localised corrosion.

The misclassification error of the test dataset was 0.12, meaning only 12 out of 100 data were misclassified by the RF model. This is in line with the result presented in Fig. 3. In other words, the classification accuracy of the RF model was 88%. Subsequently, the current RF model was employed to identify the corrosion types for the specimens buried in coal and iron ore.

In addition, the importance ($Imp$) of individual RQA variables was estimated during training of the RF model. Detailed explanation of how the $Imp$ was computed can be found in Ref. [26], but essentially the importance is linked to the decrease in performance of the model when the variable is omitted from the analysis. Variables with larger $Imp$ values are more important. As shown clearly in Fig. 4, the variables $L_{max}$ and $ENTR2$ have the highest values, and were thus the most predictive variables in the RF model.

3.2. Corrosion of carbon steel exposed to coal and iron ore

3.2.1. Identification of corrosion types for coal and iron ore

Fig. 5 shows an EN segment (after linear trend removal) obtained on the first day of the tests with coal and iron ore. It can be seen that the patterns of the segments appear to be close to those generated with sand (Fig. 2 (b)).

Similar to the EN data treatment associated with NaCl solution and sand, after segmentation and trend removal, RQA variables were extracted from the abovementioned current noise signals and
submitted to the previously developed RF model for corrosion type identification. The prediction results are displayed in Fig. 6, where each star corresponds to a current segment measured during the test. As it can be seen, the RF model predicted that during the 7-day tests the steel samples buried in iron ore and coal underwent different types of corrosion. Specifically, the iron ore mainly produced localised corrosion (98%) while the coal cargo generated both general corrosion (41%) and local corrosion (59%) corrosion on the specimens.

Table 2 shows the percentages of the current segments predicted as general corrosion and localised corrosion on a daily basis. It can be seen that localised corrosion occurred predominantly on the specimens buried in iron ore during the entire test period. In comparison, the specimens buried in coal mainly underwent
localised attack from day 1 to day 5. Afterwards, the majority of localised corrosion events seemed to cease and the specimens managed to reach a relatively stable state, with general corrosion taking place until the end of the test.

3.2.2. Post-immersion surface profilometry analysis

The prediction results presented in Fig. 6 are confirmed by the surface morphologies of the retrieved specimens, which are shown in Fig. 7(a1, a2). The specimens retrieved from the test cell with iron ore exhibited localised corrosion morphologies similar to that observed in Fig. 1(b1, b2). Fig. 7(a2) is an enlarged image of the red circled area shown in Fig. 7(a1), the deepest point of which reached 120 μm. By contrast, from Fig. 7(b1), it is clear that the entire surface area was corroded to some extent. The average surface roughness Rq (excluding pitted areas) was 4.8 μm, which was close to that observed with the specimens immersed in 0.04 wt% NaCl solution (3.6 μm). In addition, there were some local areas that showed more severe corrosion, such as the one marked by the dashed red line. An enlarged image of this area is presented in Fig. 7(b2). The 3D surface profile measurement suggested a maximum depth of 170 μm. Other locally corroded areas ranged from 100 μm to 120 μm in depth.

3.3. Discrimination of corrosion types using localisation index and shot noise parameter

3.3.1. Localisation index

Localisation index (LI) or pitting index is one of the most widely used parameters to indicate localised corrosion. It is defined as the

<table>
<thead>
<tr>
<th>Day</th>
<th>Iron ore</th>
<th>General (%)</th>
<th>Localised (%)</th>
<th>Coal</th>
<th>General (%)</th>
<th>Localised (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.6</td>
<td>96.4</td>
<td>33.3</td>
<td>66.7</td>
<td>17.8</td>
<td>82.2</td>
</tr>
<tr>
<td>2</td>
<td>1.8</td>
<td>98.2</td>
<td>17.8</td>
<td>82.2</td>
<td>11.3</td>
<td>88.7</td>
</tr>
<tr>
<td>3</td>
<td>1.8</td>
<td>98.2</td>
<td>24.8</td>
<td>75.2</td>
<td>11.3</td>
<td>88.7</td>
</tr>
<tr>
<td>4</td>
<td>1.8</td>
<td>98.2</td>
<td>32.1</td>
<td>67.9</td>
<td>11.3</td>
<td>88.7</td>
</tr>
<tr>
<td>5</td>
<td>1.2</td>
<td>98.8</td>
<td>85.1</td>
<td>14.9</td>
<td>11.3</td>
<td>88.7</td>
</tr>
<tr>
<td>6</td>
<td>1.2</td>
<td>98.8</td>
<td>77.4</td>
<td>22.6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>1.8</td>
<td>98.2</td>
<td>77.4</td>
<td>22.6</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig. 5. EN signals obtained from tests with (a) iron ore and (b) coal.

Fig. 6. Predicted types of corrosion during the 7-day tests with (a) iron ore and (b) coal by the random forest model.
standard deviation of current divided by the root mean square current [37,38]. In general, a value approaching 1 is considered as indicative of localised corrosion.

The $LI$ values for all the corrosion systems under investigation were calculated and plotted against the segment number of the current noise signals, as shown in Fig. 8. Please be reminded that the current noise data were firstly divided into continuous segments. Each segment contained 1024 data points, which is equivalent to a time frame of 512 s.

As can be seen from Fig. 8(a), from segment 300 to 400, the corrosion system with NaCl solution produced high $LI$ values (close to 1), which is an indication of localised corrosion. However, it has been shown in Fig. 1 that only uniform corrosion occurred to the steel samples. Moreover, the moist sand produced localised corrosion to the steel samples (as presented in Fig. 1), thus high $LI$ values were expected. Nevertheless, as can be seen from Fig. 8(b), all the $LI$ values were below 0.01. In addition, for the localised corrosion system generated with carbon steel buried in iron ore (Fig. 8(c)), most of the $LI$ values were below 0.4.

According to these observations, it can be concluded that the localisation/pitting index is not a reliable indicator of localised corrosion for the investigated systems.

### 3.3.2. Shot noise parameter

The characteristic frequency $f_n$ is a parameter derived from shot noise theory. It can be expressed as $f_n = \frac{B}{\psi_E A}$, where $B$ is the Stern-Geary coefficient, $\psi_E$ is the low-frequency power spectral density (PSD) of the potential noise, and $A$ is the surface area of the sample [37–39]. In this study, a value of 0.026 V per decade was used for the coefficient $B$ and $\psi_E$ was determined as the potential PSD at $10^{-1} \text{Hz}$. It is reported that uniform corrosion would have a large $f_n$, while pitting corrosion is expected to have a lower $f_n$ [39].

However, as can be seen from Fig. 9, which shows the calculated $f_n$ for the uniform corrosion system (0.04 wt% NaCl) and pitting system (iron ore), the characteristic frequency values overlap within the same frequency range. In other words, for the present study, $f_n$ is not an effective measure for the discrimination of localised corrosion and uniform corrosion processes.

### 4. Conclusions

In this study, carbon steel electrode immersed in NaCl solution (0.04 wt%) and buried in silica sand that was moistened with NaCl solution were used as references to create different types of corrosion. Surface analyses of the retrieved steel specimens from the NaCl solution and silica sand revealed two distinct corrosion types, viz. general corrosion and localised corrosion. Electrochemical current noise data collected from the reference tests were subjected to recurrence quantification analysis and the extracted
RQA variables were used as predictors to develop a random forest classification model. The RF model could discriminate between these two types of corrosion with an accuracy of 88%. Subsequently, the established model was used to identify and monitor the corrosion processes of the carbon steel specimens buried in iron ore and coal cargoes. Prediction results showed that during the 7-day tests, dominant form of corrosion to the steel specimens buried in coal at 55 °C was localised corrosion during the first 5 days, whereas general corrosion predominantly took place from day 6 onwards. By contrast, the iron ore resulted in localised corrosion (pitting) for the duration of the test. The morphologies of the retrieved steel specimens at the end of the tests agreed well with the predictions by the RF model.

The localisation index and the shot noise parameter \( f_n \) were also investigated for identification of localised corrosion. However, it was demonstrated that neither of them were effective measures for discriminating between the different corrosion processes under investigation.

The present work is an extended application and demonstration of the concepts and methodologies proposed in our previous studies [25–27]. The results yielded by this investigation further underscore the applicability of the proposed techniques. It can be expected that the combined recurrence quantification analysis of EN data and machine learning are valuable for future automated monitoring and identification of specific corrosion phenomena. Moreover, it provides a possible analytical method for investigation of the corrosive effects of cargoes on the carrier structures and can possibly be extended to corrosion under deposits with low moisture content.