Identification of Types of Corrosion through Electrochemical Noise using Machine Learning Techniques

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Abstract: Several systems in industries are subject to the effects of corrosion, such as machines, structures and a lot of equipment. As consequence, the corrosion can damage structures and equipment, causing financial losses and accidents. Such consequences can be reduced considerably with the use of methods of detection, analysis and monitoring of corrosion in hazardous areas, which can provide useful information to maintenance planning and accident prevention. In this paper, we analyze features extracted from electrochemical noise to identify types of corrosion, and we use machine learning techniques to perform this task. Experimental results show that the features obtained using wavelet transform are effective to solve this problem, and all the five evaluated classifiers achieved an average accuracy above 90%.

1 INTRODUCTION

Several very important systems in the industrial field are subject to the effects of corrosion: means of transportation, such as trains and ships, transmission towers, storage tanks, heat exchangers and boilers, reactors, etc., causing the deterioration of structures and a lot of equipment, as well as accidents (Gentil, 2003). Regarding the losses in the economic sector, corrosion can be a source of unplanned costs. The global cost of corrosion is estimated around U$ 2.5 trillion, equivalent to 3.4% of world GDP (Gross National Product) (Koch et al., 2016). Many industries have realized that the lack of corrosion management can be very expensive, and that through proper management of corrosion they can obtain significant cost reduction (Koch et al., 2016). This factor highlights the importance of developing research and technology in this field.

Fortunately, due to the simultaneous occurrence of oxidation and reduction reactions during the corrosion process, it is possible to measure the current and electrical potential fluctuations on the surfaces that are suffering this process. These measured signals are called electrochemical noise (ECN) (Fofano and Jambo, 2007).

Some types of corrosion, such as pitting, are hardly detected using traditional electrochemical techniques, however, analysis of electrochemical noise enables its identification and monitoring (Rios et al., 2013). The identification of corrosion type that is affecting the metal enables the planning and implementation of more effective solutions for the treatment and prevention in the affected areas. An example is the choice of the best inhibitor material, that can provide greater protection to the metal (Barr et al., 2001).

This work describes a methodology for the detection of corrosion types using machine learning techniques and features extracted from electrochemical noise. Machine learning is a sub-field of artificial intelligence that is compose by a set of techniques that are able to learn by examples how a task must be done. Thus, they are not programmed to do a task, but they "learn" how to do it. Machine learning (ML) techniques have been successfully utilized in various process control, monitoring and optimization applications in different industries. Some applications of ML are: tool for machine condition monitoring, fault diagnosis, image recognition to identify damaged products, food quality control, classification of polymers and several other applications (Wuest et al., 2016). However, few researches to identify types of corrosion have used this type of approach (Jian et al., 2013), being this one of the motivations of this work.

In this paper, techniques that are able to learn by example are used to detect automatically some different types of localized corrosion, such as pitting, crevice corrosion and the watermark, as well as the

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occurrence of passivation on the metal surface, which is the state in which the behavior of an electrical double layer in the solution-electrode interface forms a protective film that is resistant to corrosion (Fernandes et al., 2001). The results obtained in experiments indicate that the presented approach is promising to identify some types of localized corrosion, as well as the occurrence of passivation on metals.

The remainder of this paper is organized as follows. In Section 2, we present some useful tools in data analysis of electrochemical noise, including the wavelet transform. In Section 3, we describe basic concepts of machine learning and the classifiers used in the experiments. Subsequently, in Section 4 is shown the materials and methodology used in the measurements of potential and current of electrochemical noise. In Section 5, we present the experiments and achieved results. Our conclusions and suggestions for future work are presented in Section 6.

2 ELECTROCHEMICAL NOISE DATA ANALYSIS

ECN analysis can be performed so that the potential and current noise data are processed independently, using statistical measures, such as mean, standard deviation, kurtosis and skewness for the interpretation of the data. The relationship between the two signals can also be analyzed using the concept of electrochemical noise resistance (R_n), defined as the standard deviation of the potential σ_E divided by the standard deviation of the current σ_I, according to equation 1:

$$R_n = \frac{\sigma_E}{\sigma_I}. \qquad (1)$$

The R_n value is associated with the corrosion rate, and the higher the resistance value, the smaller the corrosion rate of the metal. The standard deviation value of the current reflect the fluctuation magnitude of the current in the system and, therefore, it can be used to estimate the corrosion activity (Cottis, 2001).

A methodology for electrochemical noise analysis, called shot noise, considers that the current has the form of a series of statistically independent charge packets, and each packet has a short duration of time. The total charge passing in a certain time interval is then a sample from a binominal distribution, and if the average number of pulses is fairly large, it approximates from a normal distribution with known properties. Applying this theory to electrochemical noise signals, three parameters can be obtained: average current of corrosion (I_{corr}), average electric charge on each event (q), and frequency of related events (f_n). These parameters are related by equation 2 (Cottis and Turgoose, 1999; Cottis, 2001).

$$I_{corr} = q f_n. \qquad (2)$$

These values cannot be measured directly, but they can be estimated from the potential and current noise data, according to equations 3 and 4 (Cottis, 2001):

$$f_n = \frac{I_{corr}}{q} = \frac{B^2}{\psi_E}, \qquad (3)$$

$$q = \frac{\sqrt{\psi_E \psi_I}}{B}, \qquad (4)$$

where ψ_E and ψ_I are the low frequency values of power spectral density of the potential and current noise, respectively. B is the Stern-Geary constant which can be estimated by Tafel's extrapolation (Cottis, 2001), where β_a and β_c are anodic and cathodic inclinations, respectively:

$$B = \frac{\beta_a \beta_c}{2.303(\beta_a + \beta_c)}. \qquad (5)$$

With the shot noise, the electric charge q involved in each case can be estimated, as well as the frequency of occurrence f_n of these events. These two parameters provide information about the nature of the corrosion process. Thus, q gives an indication of the mass of metal lost in the event, while f_n provides information about the rate at which these events occur. Therefore, a system that suffers uniform corrosion can have both the charge and frequency elevated. For localized corrosion systems, a low frequency and a high charge is expected. In the case of passivation, the charge is low and the frequency depends on the process that is occurring in the passive film (Amaya et al., 2005).

A problem of this approach is the Stern-Geary constant B, whose value can be estimated by Tafel constant (Equation 5). Several experimental disadvantages can be associated with Tafel plots. For example, relative large potential range used in Tafel extrapolation can cause changes in the metal surface, disabling the electrode, requiring the use of two metal specimens for complete Tafel plot (Research, 1980). In some cases, such as corrosion of steel in concrete, the value of B is not constant and can be estimated by LPR (Linear Polarization Resistence), without Tafel plots (Poursaee, 2010). Nevertheless, this technique requires an specific instrumentation use, and does not provide sufficient information to detect and distinguish different types of localized corrosion (Cox, 2014).

Other more recent techniques of ECN analysis include the use of tools as Fourier Transform, Wavelet Transform and concepts of chaos theory (Fofano and Jambo, 2007; Planinsic and Petek, 2008). The biggest advantage of using ECN on the analysis of corrosive processes, compared to traditional electrochemical techniques, is the ability to identify the type of corrosion present on the studied solid surface (Cottis, 2001). Thus, the ECN appears as a promising technology in monitoring corrosion able to provide accurate information in real time, replacing the conventional LPR instrumentation (Cox, 2014).

The biggest challenges in the analysis of electrochemical noise are related to the stochastic nature of the corrosion process, which results in most cases in nonstationary signals. The nonstationarity of electrochemical noise signals can be observed in two primary ways: by fluctuations in the variation of the potential or current and by the variation of statistical properties of the signal over time. This signal characteristic imposes some limitations on the use of Fourier Transform, since it does not take into account the variation of the frequency content over time. One approach that has been used for ECN analysis is the wavelet transform. This method overcomes the limitations of the Fourier transform, since it enables the decomposition of the signal into diferente frequency components for different time intervals (Cottis et al., 2015).

2.1 Wavelet Transform Analysis

In conventional Fourier analysis is not possible to find in what period of time certain frequency band of a signal occurred, because this information is lost during the transform. A way to overcome this problem is to use the wavelet transform. The most general principle in the construction of wavelets is the use of dilations and translations, and the most commonly used form is an orthonormal function system (Aballe et al., 1999). Wavelet can distinguish the local characteristics of a signal on different scales and, by translations, they cover all the region in which the signal is studied. This locality property of wavelets is an advantage over the Fourier Transform in the analysis of nonstationary signals, being a more efficient tool, and applicable to the study of electrochemical noise signals (Aballe et al., 1999; Cottis et al., 2015).

For the analysis of discrete signals from sampled corrosive processes, the Discrete Wavelet Transform (DWT) is conventionally used to obtain the coefficients values of different frequency bands for each time interval. These values are obtained by convolution of the sampled signal by functions that are displaced and dilated versions of a wavelet function (or mother wavelet). Thus, the original signal can be written as a sum of wavelet functions ($\phi_{J,n}(t)$ e $\psi_{J,n}(t)$) weighted by their corresponding coefficients, called detail ($d_{J,n}$) and smooth coefficients ($s_{J,n}$). These coefficients indicate the correlation between the wavelet function and the corresponding signal segment (Aballe et al., 1999). As show by the equations 6, 7 and 8:

$$x(t) \approx \sum_n s_{J,n} * \phi_{J,n}(t) + \sum_n d_{J,n} * \psi_{J,n}(t) + \sum_n d_{J-1,n} * \psi_{J-1,n}(t) + \ldots + \sum_n d_{1,n} * \psi_{1,n}(t), \tag{6}$$

$$s_{J,n} = \int x(t)\phi^*_{J,n}(t)dt, \tag{7}$$

$$d_{J,n} = \int x(t)\psi^*_{J,n}(t)dt, \tag{8}$$

where $n = 1...N$, N is the length of the discrete signal and J stands for the decomposition level of DWT.

The coefficient matrix generated by DWT can be difficult to interpret for some ECN signals. A more useful way to represent the results of the wavelet transform in the analysis of electrochemical noise is through the concept of coefficient energy distribution. Thus, the contribution of each energy level of decomposition is calculated regarding the total energy of the signal. In this context, the signal energy may be calculated by (Aballe et al., 1999):

$$E = \sum_{n=1}^{N} x_n^2, \tag{9}$$

where E is the total energy of signal, x_n is the signal values in the instants $n = 1, 2, 3, ..., N$ and N is the length of the discrete signal.

From the total energy E, the fraction of energy of each detail coefficient (E_j^d) and of smooth coefficient (E_j^s) can be calculated, respectively, according to equations 10 and 11, where J are the levels used in the decomposition of the signal through the DWT.

$$E_j^d = 1/E \sum_{n=1}^{N/2j} d_{j,n}^2. \tag{10}$$

$$E_j^s = 1/E \sum_{n=1}^{N/2j} s_{j,n}^2. \tag{11}$$

Another recently developed ECN analysis tool is the concept of entropy associated with wavelet transform (Moshrefi et al., 2014). While the transform coefficients indicate the transient behavior of the signal, the concept of entropy is used to measure this degree of variability. Thus, the concept of entropy based on wavelet analysis reveals the degree of order/disorder of ECN signals, which will vary according to the conditions of the corrosion process. The entropy of a discrete random variable x with probability $p(xi)$ can be defined by:

$$H(x) = -\sum_{i=1}^{n} p(x_i) log(p(x_i)), \tag{12}$$

where $p(x_i)$ is estimated as the kernel density.

As the energy, entropy of the wavelet transform decomposition levels provides information to analyze the ECN signals that cannot be obtained through temporal analysis of the signals, making it a powerful tool for corrosive behavior detection (Moshrefi et al., 2014).

The wavelet transform is considered a good tool for the extraction of useful features of ECN signals, since each transform coefficient is associated with the signal characteristics at a particular frequency band, and its application has resulted in several relevant works for the study of corrosion. Wavelet analysis of electrochemical noise signals was used to characterize the intensity of the occurrence of pits on the surface of steel (Smulko et al., 2002). Wharton et al. has demonstrated how the wavelet variance can be used to evaluate the corrosion behavior for a variety of stainless steels in chloride medium, allowing the distinction between the many corrosion processes (Wharton et al., 2002). In 2007, Jong Jip Kim used ECN wavelet transform to identify the evolution of the types of corrosion on the stainless steel surface: general corrosion, metastable pitting and stable pitting, so that each identified type is related to the energy distribution of coefficients obtained through transform (Kim, 2007).

3 Machine Learning

Extraction of relevant features of ECN signals is the first step for automatic classification of the types of corrosion that affect the surface of a metal. One of the tools that can be used in the classification is Artificial Neural Networks (ANN) and the basic steps of this approach can be seen in Figure 1.

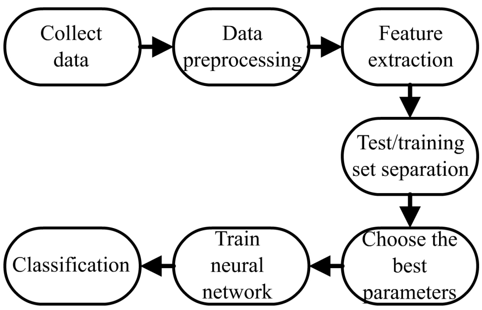


Figure 1: Basic flowchart of classification using ANN.

The work developed in (Jian et al., 2013) is one of the few studies known by the authors that used machine learning techniques to identify types of corrosion through ECN. In that study, features extracted from ECN signals were used to train an ANN type MLP (Muti-Layer Perceptron) and SVM (Support Vector Machine) to perform automatic classification of types of corrosion that occur on the surface of stainless steel: pitting and general corrosion, as well as the identification of passivation (Jian et al., 2013). In this work, five classifiers will be evaluated, including MLP and SVM, to identify three types of localized corrosion (pitting, crevice corrosion and watermark), as well as the occurrence of passivation on carbon steel AISI / SAE 1040. The evaluated classifiers are presented in the following subsections.

3.1 MLP

MLP is an artificial neural network composed by a set of processing units (artificial neurons) forming an input layer, one or more intermediate layers (hidden) and an output layer. Their training is supervised and an algorithm of back propagation of error is used to adjust their weights in order to minimize the distance between the network response and the desired response (Haykin, 1998).

3.2 Probabilistic Neural Network

Probabilistic Neural Network (PNN) is a type of neural network whose transfer functions are gaussian functions centered on training samples, which allows the association between the network structure and probability density functions. In other words, PNN provides as output the probability of the input pattern to belong to each class. PNN uses the concept of Parzen estimators and with enough data converges on the Bayesian Classifier (Masters, 1995).

3.3 kNN

k nearest neighbor (kNN) is a technique of classification based on distance (Duda et al., 2000). The learning in this classifier is based on analogy. To determine the class of an input pattern, kNN searches the k samples of the training set that are nearest to the input, that is, those with the smallest distances. There are several distance metrics, and the Euclidean distance is the most common. Equation 13 shows this metric, where x and y are two samples with n features.

$$d(x,y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}. \tag{13}$$

3.4 Decision Tree

Decision trees are algorithms used in the classification of patterns based on the idea of “divide and conquer”:

a complex problem is decomposed into simpler subproblems and the same strategy is applied recursively to each subsub-problem. Thus, the ability of description of a tree comes from dividing the space defined by the feature in subspaces, where each subspace is associated with a class. The starting point of a decision tree is called the root node and consists of all the learning set, and it is at the top of the tree. A node is a subset of the features set, and can be terminal (leaf node) or non-terminal (division node). In the training process of the tree, the division criterion must be maximized until a subset is associated with a class (Quinlan, 1988).

3.5 SVM

Support Vector Machines (SVM) is a machine learning technique based on mathematical optimization and statistical learning theory. SVM is also based on the idea of separation of data through hyperplanes to determine the class of each sample. To ensure the inherent convexity of the optimization problem in the process of SVM learning, it is necessary to choose the kernel function that best fits the problem. In this work is used linear kernel because of its simplicity.

To design the SVM is necessary to determine three parameters: the cost (c), the kernel function, and kernel parameters, but in the linear kernel does not exist parameter. The cost is a constant of tolerance to error, that is, the higher the cost value, the less the error can be tolerated by learning (Theodoridis and Koutroumbas, 2008).

4 MATERIALS AND METHOD TO COLLECT THE DATA

Corrosion analysis, through signal processing, consists in the mounting of an experimental apparatus, called electrochemical cell, and an A/D (analog/digital) converter is used for the measurements of electrochemical noise. In this work, potential signals were measured and stored and, indirectly, current signals. Electrochemical cell is an experimental apparatus consisting of an inert metal immersed in an aqueous solution containing ions in different oxidation states. The cell used in this study consists of two steel electrodes AISI 1040 used as working electrodes and counter electrodes. These electrodes are nominally identical and coated with termocontract, and they have exposed area to solution equal to $499,512 mm^2$. The reference electrode used to collect data was $Ag/AgCl$. Through the A/D converter interface is connected to the electrochemical cell, with the

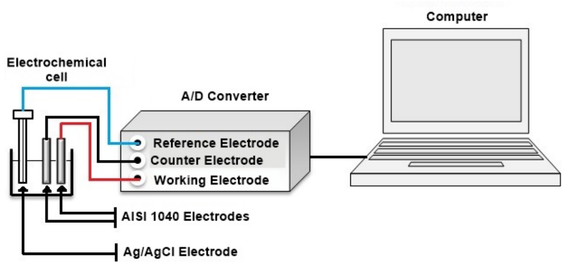


Figure 2: Experimental apparatus configuration.

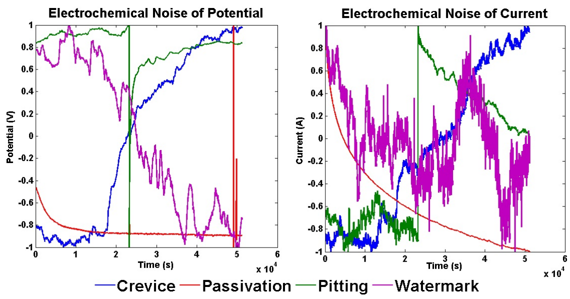


Figure 3: Collected Electrochemical Signals in Same Scale.

computer, you can store and perform math operations on the data. Figure 2 shows a diagram with the instruments used for data collection and Figure 3 shows the ECN signals collected.

According to the American Institute of Iron and Steel and International Society of Automotive Engineers, 1040 steel consists of about 0.37 to 0.44% carbon (C) 0.6 to 0.9% manganese (Mn) of at most 0.040% phosphorus (P) and 0.050% sulfur (S). Among the metals used in the industry, carbon steel 1040 has a wide range of use. Its main applications are in mechanical components such as gears, shafts, crankshafts, camshafts, guide pins, gear rings, columns, turnstiles, cases, construction of oil and gas pipelines. These structures are subject to corrosion, and tragic consequences may occur for people who work in the vicinity of such equipment (Gentil, 2003). To collect the data, steel electrodes were immersed for 24 hours in passivation solution Na_3PO_4 with concentration of 0.02 M (mol/L), and sampling frequency of 1 Hz. After that time, the $NaCl$ solution was added with a concentration of 0.34 M to start the experiment in aggressive solution for a period of approximately 120 hours and sampling frequency of 1 Hz. All measurements were obtained at room temperature. The formation and growth of passive film and the occurrence of corrosion were analyzed using the potential and current of the noise according to immersion time. The electrochemical noise signals of the current and potential were recorded by an A/D converter.

5 RESULTS AND DISCUSSION

The experiments were divided into two phases. In the first phase, the most relevant features were selected to identify the types of corrosion. This step is important to reduce the computational cost and improve the performance of classifiers. In the second phase, the classification algorithms are trained with the features found to identify the occurrence and type of corrosion. In both phases, the accuracy metric was used as quality measure. The value of the accuracy is calculated by the ratio of the number of samples correctly classified by the total number of samples, multiplied by 100%. The higher the value of accuracy, the better. The best value is 100%.

5.1 Feature Selection

In this phase, the following features (and respective dimensions) were evaluated: detail and smooth coefficients (10 elements each), energy (8 elements), entropy (9 elements), ratio between standard deviation and mean (1 element), kurtosis (1 element), ratio between the derivative and the mean (1 element), and resistance to electrochemical noise (1 element). Each characteristic was extracted for both voltage and current signals, except resistance to electrochemical noise. Thus, the full feature vector to be analyzed by the SBS has 81 elements. The Wavelet Transform of Daubechies (db4) with decomposition at 8 levels was used to compute the energy and entropy, as described in Section 2.1, in addition to detail and smooth coefficients. The main property of the Daubechies function is that it is a wavelet highly localized in time, which is good for electrochemical noise studies, where short time duration events are the norm (Bertocci et al., 1997). The features were obtained from non-overlapping data packets composed of 1024 points of ECN signals of potential and current.

For the selection of the most significant features, we used SBS algorithm (Sequential Backward Feature Selection), which is a search algorithm that starts with a complete set of features and for each iteration removes the feature with the least impact on the established criterion function (in this paper we used accuracy). Multidimensional features has been analyzed as a group, not individually.

SBS was applied along with a MLP with 20 neurons in the hidden layer, learning rate equal to 0.001 and 1000 training epochs using Levenberg-Marquardt algorithm (Marquardt, 1963) for training. For this experiment, a training set of 132 samples and a test set with 68 samples were used, totaling 200 examples selected of different parts of the sampled signal, while ensuring there is the same number of samples for all four classes. The features were normalized by the mean and standard deviation obtained from the training set, so that the distribution of each feature has zero mean and standard deviation equal to one.

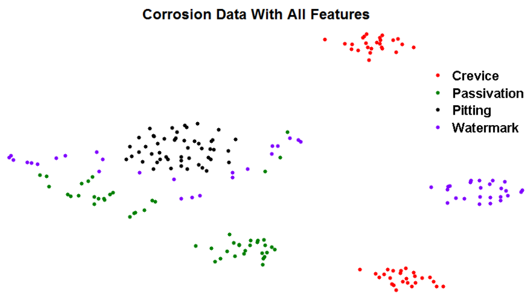
The attributes selected by the SBS were: entropy, energy, and resistance to electrochemical noise, resulting in a feature vector of 35 elements (8 entropy and 9 energy for each voltage and current signal, and one resistance of the electrochemical noise).

In Figure 4 is shown in 2D graphics how good the selected features are to separate the samples of the different types of corrosion. Figure 4(a) shows the separation using all features and 4(b) using only the selected features. As we can see, the separation using the selected features is clearer than using all features. A dimensionality reduction technique is necessary to visualize this graphics, whose mapping hold neighborhood relations in the dataset, i.e., if a p instance is neighbor of q in the original space, the mapped point p must also be neighbor of q in reduced dimensional space. For this porpose, we used t-Distributed Stochastic Neighbor Embedding Technique (t-SNE), which produces one of the best mappings in terms of preserving neighborhoods (Fadel et al., 2015). t-SNE is a dimensionality reduction technique based on probabilities that aims to position multidimensional data in two-dimensional space, preserving local structures. In this technique, similarities between pairs of instances in the original space are modeled as a distribution of t-student probabilities. More specifically, the more similar two elements are, the higher the probability associated with them. Similarly, the distances between pairs of projected points are also modeled as a probability distribution.

Two points must be highlighted here. First, although the ratio between the number of samples and the number of features is low, we can see in Figure 4(b) that the separations among the classes are almost linear, so complex surfaces are not required for class separation, and even simple models, such as decision trees, can perform the task properly with few samples. Second, although the selected features may favor the MLP algorithm more than the other ones, previous experiments have indicated that some of the evaluated features, such as those based on statistics, are not very useful for this task, and probably other algorithms could have selected the same set of features.

5.2 Corrosion Type Determination

To verify if the selected features have a good ability to distinguish the different types of corrosion, the next step is the training of the classifiers presented in Sec-



(a)

(b)

Figure 4: Features visualization using t-SNE. Visualizing corrosion data with (a) all features and (b) selected features.

tion 3. Initially, 48 samples for each one of the four types of corrosion were obtained, each one composed of the 35 features selected in Section 5.1. The features were extracted from non-overlapping data packets of 1024 points each, from potential and current signals. These packages were selected from different parts of the sampled signal (which were different to those used in Section 5.1). After this step, the samples were stratified into 3 folds of data, each one with 64 samples. Then, for each classifier were obtained 3 results from 3 tests, and each result was achieved using 2 folds for training/validation and 1 fold for testing. For each result was used a different fold for testing. The features were normalized by the mean and standard deviation, as described in Section 5.1.

The following configurations were tested for each technique in order to maximize the accuracy on the training set and, possibly, also on the test set. MLP was trained using Levenberg-Marquardt algorithm, learning rate of 0.001, 1000 epochs and evaluated different numbers of neurons in the hidden layer (1 to 50 neurons). Different values of standard deviation were tested for PNN (0.1 to 1.0, with steps of 0.1). For kNN, we employed Euclidean distance and we varied the value of k (1 to 10). The SVM used in the experiments had linear kernel, and different values of cost c were evaluated (0 to 10, with steps of 0.5). For the decision tree was used the standard Matlab implementation, which does not have parameters to tune. For each test, the parameters of each technique were adjusted in order to maximize the accuracy on the training folds, and these parameters were used to classify the samples of the test fold. Table 1 shows the values of the parameters selected for each test fold and for each classifier.

Table 1: Selected parameter for each classifier.

Test	MLP Neurons	PNN Standard deviation	kNN k neighbors	SVM Cost
1	28	0.3	1	2
2	37	0.2	4	0.5
3	5	0.2	1	0.5

Table 2 shows the values of the accuracy obtained by each technique in each test fold, and the best result for each fold was highlighted. The features were normalized by the mean and standard deviation obtained from the training set. As can be seen, all algorithms have achieved an average accuracy above 95%, with the exception of the decision tree. SVM achieved mean accuracy slightly better than those obtained by the other classifiers, followed by MLP. kNN and PNN, which are simpler techniques to implement, achieved results as good as SVM. Therefore, they are an option for cases where simplicity is more valuable than performance. Decision tree achieved high accuracy value for the first and third test folds, but for the second test fold it did not achieve the same performance. Some reasons may have been the construction of a tree with little capability of generalization and the fact that the process of feature normalization, through mean and standard deviation, have no effect on the decision trees. However, the high accuracy values in other classifiers indicate that this methodology was effective to identify the types of corrosion analyzed.

Table 2: Classification results of each technique with normalization (accuracy values are in percent).

Test	MLP	PNN	kNN	Tree	SVM
1	95.59	97.66	95.31	**100.00**	**100.00**
2	**100.00**	**100.00**	**100.00**	78.13	**100.00**
3	95.31	92.97	92.19	**96.88**	92.26
Mean	96.97	96.88	95.83	91.67	**97.42**
Std. Dev.	**0.02**	0.03	0.03	0.11	0.04

In Table 3 is shown the results of the same experiment, but the features were not normalized. As we can see, the average accuracy of each classify is slightly lower than the results shown in Table 2. Thus, normalized features help to improve the results. However, all techniques in Table 3 achieved an average accuracy above 90%. Furthermore, as can be observed, the accuracy of the decision trees are the same in both tables, because normalization has not effect on them.

Table 3: Classification results of each technique without normalization (accuracy values are in percent).

Test	MLP	PNN	kNN	Tree	SVM
1	92.28	99.22	95.31	**100.00**	96.87
2	**95.44**	88.28	93.75	78.13	93.75
3	94.41	94.66	92.69	**96.88**	95.31
Mean	95.04	94.05	93.92	91.67	**95.31**
Std. Dev.	0.03	0.06	**0.01**	0.11	**0.01**

The results using the selected features were compared to the results obtained with the features used in (Jian et al., 2013), which is one the few studies known by the authors that uses features extracted from ECN signals to train a machine learning technique. The features used in (Jian et al., 2013) were the electrochemical noise resistance (R_n), the frequency of events (f_n), the charge (q) and the energy of the detail coefficients extracted by wavelet transform. Using these features were obtained the results in Table 4, when employing the same previous procedure to train/validate and test the classifiers (using the same dataset). The comparison between Tables 2 and 4 indicates that the features used in this work are more effective to identify correctly the types of corrosion. The main difference between the two approaches is the use of entropy information. In (Jian et al., 2013) is used the Stern-Geary constant, but it can be a great source of error if this value is not precisely estimated (Ahmad et al., 2014). Moreover, this value is not constant in some cases (Poursaee, 2010).

Table 4: Classification results of each technique using the features employed in (Jian et al., 2013) (accuracy values are in percent).

Test	MLP	PNN	kNN	Tree	SVM
1	**89.06**	84.38	73.44	70.31	71.87
2	85.15	**89.84**	82.81	76.56	85.93
3	76.56	**78.13**	70.31	64.06	53.12
Mean	83.59	**84.11**	75.52	70.31	70.31
Std. Dev.	0.06	**0.05**	0.06	0.06	0.16

For a better analyze of the results, the average accuracy of the SVM in Table 2 is shown in a confusion matrix (Figure 5). Each column in this matrix is a output class and each row is a target class. In the diagonal of matrix (in green) are shown the outputs that are equal to the target classes. The red elements indicate the wrong outputs. The gray boxes are the accuracy of each corrosion type, and the blue box is the average accuracy of the SVM. The numbers 1, 2, 3 and 4 indicate the crevice, passivation, pitting and watermark classes, respectively. Observing the confusion matrix is possible to identify that only 5 samples belonging to pitting class were wrong classified as watermark by the SVM. This error could be expected by inspecting Figure 4(b), where we can see a little separation margin between pitting and watermark.

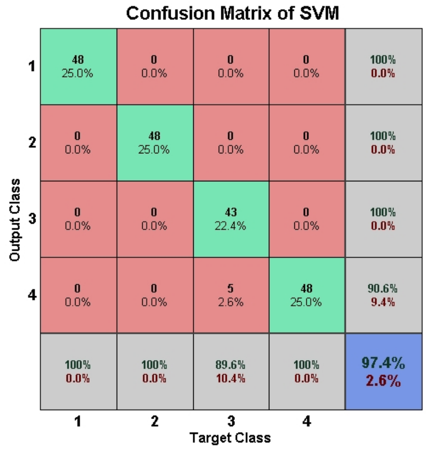


Figure 5: Confusion matrix of SVM.

6 CONCLUSIONS

This paper presented an approach to identify some types of corrosion on metal surface through electrochemical noise signals. In experimental results was observed that resistance to electrochemical noise and features extracted from wavelet transform, entropy and energy, were the most discriminative for this task. After analyzing the results for the five evaluated classifiers, we noted that all five algorithms had achieved an average accuracy above 90% to perform the task, and SVM achieved an average accuracy slightly better than those obtained by the other classifiers for identifying types of corrosion. Therefore, the results of this study highlight the importance of using wavelet transform for electrochemical noise analysis. In future work, we intend to analyze other algorithms and other features in order to improve the results using only a type of signal, simplifying the instrumentation necessary to collect the data.

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REFERENCES

Aballe, A., Bethencourt, M., Botana, F., and Marcos, M. (1999). Using wavelets transform in the analysis of electrochemical noise data. In *Electrochimica Acta*. Elsevier.

Ahmad, S., Jibran, M. A. A., Azad, A. K., and Maslehuddin, M. (2014). A simple and reliable setup for monitoring corrosion rate of steel rebars in concrete. *The Scientific World Journal*, page 10.

Amaya, J., Cottis, R. A., and Botana, F. (2005). Shot noise and statistical parameters for the estimation of corrosion mechanisms. In *Corrosion Science*. Elsevier.

Barr, E., Greenfield, A., and Pierrard, L. (2001). Application of electrochemical noise monitoring to inhibitor evaluation and optimization in the field: Results from the kaybob south sour gas field. In *Corrosion*. NACE international.

Bertocci, U., Gabrielli, C., Huet, F., and Keddan, M. (1997). Noise resistance applied to corrosion measurements. In *Electrochemical Society Journal*. electrochemical Society.

Cottis, R. (2001). Interpretation of electrochemical noise data. In *Corrosion*. NACE international.

Cottis, R. and Turgoose, S. (1999). *Corrosion Testing Made Easy: Impedance and Noise Analysis*. NACE International, Houston, 1nd edition.

Cottis, R. A., Homborg, A., and Mol, J. (2015). The relationship between spectral and wavelet techniques for noise analysis. In *Electrochimica Acta*. Elsevier.

Cox, W. M. (2014). A strategic approach to corrosion monitoring and corrosion management. *Procedia Engineering*, 86:567–575.

Duda, R., Hart, D. G., and Stork, P. (2000). *Pattern Recognition*. Wiley Interscience, New York, 1nd edition.

Fadel, S. G., Fatore, M., Duarte, S., and Paulovich, V. (2015). Loch: A neighborhood-based multidimensional projection technique for high-dimensional sparse spaces. In *Neurocomputing*. Elsevier.

Fernandes, J., Kubota, L., and Neto, G. (2001). Ion-selective eletrodes: historical, mechanism of response, selectivity and concept review. In *Quimica Nova*. Scielo.

Fofano, S. and Jambo, H. (2007). *Corrosion: fundamentals, monitoration and control*. Ciencia Moderna, Brazil, 1nd edition.

Gentil, V. (2003). *Corrosion*. LTC, Brazil, 1nd edition.

Haykin, S. (1998). *Neural Networks: A Comprehensive Foundation*. Prentice Hall, Canada, 2nd edition.

Jian, L., Weikang, K., Jiangbo, S., Ke, W., Weikui, W., Z.Weipu, and Zhoumo, Z. (2013). Determination of corrosion types from electrochemical noise by artificial neural networks. In *international Journal of Electrochemical Science*. Electrochemical Science.

Kim, J. (2007). Wavelet analysis of potentiostatic electrochemical noise. In *Materials Letters*. Elsevier.

Koch, G., Varney, J., Thompson, N., Moghissi, O., Gould, M., and Payer, J. (2016). International measures of prevention, application and economics of corrosion technologies study (impact). In *Technical report*. NACE international.

Marquardt, D. W. (1963). An algorithm for least-squares estimation of nonlinear parameters. *Journal of the Society for Industrial and Applied Mathematics*, 11(2):431–441.

Masters, T. (1995). *Advanced algorithms for Neural Networks: A C++ Sourcebook*. John Wiley and Sonsl, New York, 1nd edition.

Moshrefi, R., Mahjani, M., and Jafarian, M. (2014). Application of wavelet entropy in analysis of electrochemical noise for corrosion type identification. In *Electrochemistry Communications*. Elsevier.

Planinsic, P. and Petek, A. (2008). Characterization of corrosion process by current noise-based fractal and correlation analysis. In *Electrochimica Acta*. Elsevier.

Poursaee, A. (2010). Potentiostatic transient technique, a simple approach to estimate the corrosion current density and stern-geary constant of reinforcing steel in concrete. *Cement and Concrete Research*, 40(9):1451–1458.

Quinlan, J. (1988). *Decision trees and multivalued attributes*. Oxford University Press, New York, 11nd edition.

Research, E. P. A. (1980). Basics of corrosion measurements - application note corr-1. Technical report, Princeton.

Rios, E., Zimer, A., Pereira, E., and Mascaro, L. (2013). Analysis of aisi 1020 steel corrosion in seawater by coupling electrochemical noise and optical microscopy. In *Electrochimica Acta*. Elsevier.

Smulko, J., Darowicki, K., and Zielinski, A. (2002). Pitting corrosion in steel and electrochemical noise intensity. In *Electrochemistry Communication*. Elsevier.

Theodoridis, S. and Koutroumbas, K. (2008). *Pattern Recognition*. Elsevier, San Diego, 4nd edition.

Wharton, A., Woo, R. J. K., and Mellor, B. G. (2002). Wavelet analysis of electrochemical noise measurements during corrosion of austenitic and superduplex stainless steels in chloride media. In *Corrosion Science*. Elsevier.