Review of Artificial Neural Networks (ANN) applied to corrosion monitoring

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Abstract. The assessment of corrosion within an engineering system often forms an important aspect of condition monitoring but it is a parameter that is inherently difficult to measure and predict. The electrochemical nature of the corrosion process allows precise measurements to be made. Advances in instruments, techniques and software have resulted in devices that can gather data and perform various analysis routines that provide parameters to identify corrosion type and corrosion rate. Although corrosion rates are important they are only useful where general or uniform corrosion dominates. However, pitting, inter-granular corrosion and environmentally assisted cracking (stress corrosion) are examples of corrosion mechanisms that can be dangerous and virtually invisible to the naked eye. Electrochemical noise (EN) monitoring is a very useful technique for detecting these types of corrosion and it is the only non-invasive electrochemical corrosion monitoring technique commonly available. Modern instrumentation is extremely sensitive to changes in the system and new experimental configurations for gathering EN data have been proven. In this paper the identification of localised corrosion by different data analysis routines has been reviewed. In particular the application of Artificial Neural Network (ANN) analysis to corrosion data is of key interest. In most instances data needs to be used with conventional theory to obtain meaningful information and relies on expert interpretation. Recently work has been carried out using artificial neural networks to investigate various types of corrosion data in attempts to predict corrosion behaviour with some success. This work aims to extend this earlier work to identify reliable electrochemical indicators of localised corrosion onset and propagation stages.

1. Introduction
The University of Northampton has a small group of academic experts who combine to provide courses and research in condition monitoring. Much of the work carried out by this group comes under the umbrella of monitoring and assessing materials degradation by conventional methods used in engineering industries such as the power industry, aviation, railways and other safety critical applications. However, within the group are experts in electrochemical monitoring and advanced computer applications especially neural networks.

An example of this research was a work package within an EPSRC project, SuperGen II, conducted at Cranfield University by the author [1]. The SuperGen II project had industrial and academic partners, with the aim of furthering technology that could target specific industrial problems such as corrosion rates and more importantly corrosion mechanisms. The work examined the possible application of electrochemical noise monitoring to high temperature materials degradation in a power
plant. This involved the production of specialised probes to be incorporated into a pilot power plant to monitor the effects of bio-mass fuel additions on corrosion rates of boiler tubes. The scope of the project limited the amount of data analysis that could be done, but results showed that the use of electrochemical noise as a monitoring tool can be extended further than just low temperature aqueous corrosion studies. Analysis of data from the high temperature tests showed differences between the data set distributions depending on the corrosion mechanism. The trends in corrosion rate evaluated from the electrochemical noise data, due to changes in environment and temperature change, corresponded with those expected but quantitative results were not established during this work. Two International conference papers were also published from this work [2,3]. Additional work using advanced computing techniques within this group has been conducted with the British Institute of Nondestructive Testing. This has led to an interest in ultrasonic modelling and the use of AI techniques to automate some of the test procedures.

2. Introduction to present research

Condition monitoring is designed into many engineering systems where service life and safety are an issue. The assessment of corrosion within an engineering system often forms an important aspect of condition monitoring but it is a parameter that is inherently difficult to measure and predict. The electrochemical nature of the corrosion process allows precise measurements to be made and advances in instruments, hardware and software have resulted in many devices that can gather data and perform various analysis routines to provide parameters for corrosion types and corrosion rates [4]. The data often originates from adapted laboratory techniques such as Linear Polarisation Resistance (LPR) measurements, Polarisation scans, impedance measurements and spectroscopy and more recently Electrochemical Noise (EN). Many of the instruments require a good understanding of corrosion theory if they are to be set-up correctly and the output from these devices is only as good as the information supplied by the operator during the set-up of software parameters. An example of this is the common practice of estimating Tafel constants. Corrosion rates [5] and service lifetimes are one of the biggest challenges for condition monitoring applied to complex engineering plants and much effort has gone into predicting this often without a full understanding of the fundamental mechanisms at work. Although corrosion rates are important they are only useful in situations where general or uniform corrosion dominates, and even then the assumption has to be made that the behaviour is linear or a corrosion coefficient must be established.

In many situations general corrosion is not an issue because of the nature of the metal alloys themselves or the environment in which they operate. However, in these conditions a more dangerous form of corrosion that is localised and often invisible until too late can be produced [6]. Pitting, inter-granular corrosion and environmentally assisted cracking (stress corrosion) are examples of these mechanisms that can be extremely dangerous in certain systems. Previously sound metal can become unstable on a microscopic scale due to changes in local conditions at the metal surface interface ranging from chemical changes to mechanical changes in the metal surface. Electrochemical techniques can be very efficient at detecting the onset of these mechanisms in laboratory conditions but often the data requires expert interpretation and even then this can be open to debate [7]. Polarisation scans are often used to detect the onset of pitting corrosion and establish parameters for safe operating envelopes where re-passivation will prevail should a pit form. Electrochemical Noise (EN) has also been used with some success to determine the onset of pitting and stress corrosion cracking on various alloys [8]. The main problem with EN has always been interpretation of the data and different workers have applied many different treatments to the data sets in attempts to obtain information about the corrosion system [9,10].

EN is seen as a very useful technique as it is the only truly non-invasive electrochemical corrosion monitoring technique and with modern instrumentation extremely sensitive to changes in the system. This can be especially important when investigating sensitive systems and coated substrates [11]. In addition to this, the experimental procedure or data gathering techniques are relatively simple and fast compared with some of the other techniques. Over recent years the configurations for obtaining EN
data have been developed to a point where the technique could be applied outside of the laboratory to real engineering systems without major considerations in the design of probes or other methods of obtaining the data [12]. These new configurations have been proven in the laboratory and although there is still work to do on the underlying mechanisms they can be used with confidence.

Analysis of EN data in its simplest form involves visual observation of the timeline plots of potential and current data obtained from the corrosion cell. Transients produced by pitting and increased corrosion activity can be identified relatively easily in the data sets by an experienced eye [13] but may be misinterpreted or missed by less experienced observers. More sophisticated treatments have involved analysis by statistical techniques using calculated parameters such as current noise ($I_n$) and potential noise ($V_n$) based on standard deviation values of the two independent data sets obtained during data logging [14]. Building on this area of data treatment various relationships have been established between parameters to produce measures such as noise resistance ($R_n$) and RMS values. Relationships between electrochemical noise and other parameters have seen applications with localised corrosion mechanisms through the pitting index [15]. Much of this work has been applied to organic and anti-corrosion coatings and more recent work by the author has adapted the technique to high temperature applications. In this instance hot corrosion was the dominating mechanism on heat exchanger alloys. Statistical analysis was used to examine data from the high temperature tests along with examination of data distributions using kurtosis analysis [3]. These techniques put a numerical value on the shape of the data distribution assuming it is a Gaussian distribution. Other workers have argued that these values could indicate localised corrosion in aqueous corrosion cells [16] and as such an attempt was made to establish this relationship in high temperature data sets.

The data treatments described are all classified as time-line analysis as the parameters are derived with respect to the original data sets; current or potential verses time. In addition much work has been done on EN data by using transforms such as Fourier and maximum entropy to convert information into the frequency domain. Parameters such as $V_{sn}$ and $I_{sn}$ have been derived from transforms of the original potential and current data sets into the frequency domain. These have been used previously to identify localised corrosion mechanisms [17] and have been correlated with time domain parameters and compared with EIS data.

3. Review of present research

In most instances, as stated previously, the values from these parameters need to be used with conventional theory to obtain meaningful information which relies on expert interpretation. Over recent years work has been carried out using artificial neural networks. The most commonly used network is the multi-layered perceptron (MLP), primarily because it has been shown that the MLP can approximate any input-output mapping or function [18]. These ANNs used various types of data in attempts to predict corrosion behaviour. Work using various environmental variables that cause non-linear behaviour were investigated recently [19]. The environmental factors in this case were temperature, acidity and exposure time along with surface morphology of the metal and interaction between them. Real mass loss data was compared from tests at different geographical locations. Using so called “dose-response” (D/R) functions, derived using the environmental conditions, calculated mass losses were also derived using two different functions and a third set of data produced using an ANN model. Across seven different sites the ANN model produced closer results to the real mass loss data than either two of the D/R functions. Other work based on atmospheric variables and using ANN to predict corrosion rates was carried out on metals used in high voltage power transmission in Brazil [20]. Low carbon steel, aluminium and copper were studied over a transmission line covering 200km. Results were comparable with those obtained from exposure specimens indicating that the ANN was a good indicator of corrosion rates in these circumstances. Earlier work [21] also used ANN analysis to predict corrosion behaviour. This work investigated systems with environmental variables including temperature, time of wetness, exposure time and concentrations of sulphur dioxide and chloride. The database used for this work included information from corrosion tests around the World totalling thirty
three countries. Materials investigated in this work were steel and zinc and it was shown that the ANN results accounted for approximately 70% of the variance seen in the real data sets.

More recent work using ANN analysis has included the prediction of time to failure of 304 stainless steel by stress corrosion cracking. This work also used variables such as temperature and chloride concentration, but had the extra parameter of applied stress included in the data base values [22]. The application of ANN to electrochemical testing by predicting impedance spectroscopy values has been used by workers investigating corrosion inhibition of pipeline steel [23]. In this case the model’s aim was to predict the imaginary impedance based on the real part of the impedance as a function of time.

ANN analysis and the incorporation of the model into the software in an instrument to provide reliable information about localised corrosion mechanisms would be a useful area to investigate. Most recently workers have applied ANN analysis to interpreting data from electrochemical noise tests [24]. In this work a relatively new experimental configuration for obtaining electrochemical noise data was used. The paper claimed that this technique was an adoption of the “No connection to substrate” (NOCS) technique, although in practice it was actually much closer to a technique developed by this author where the standard set-up is electrically reversed and the substrate is used as a pseudo-reference. This technique was termed the single substrate technique [25] due to the fact that one substrate element could be used with the electrochemical noise test as opposed to the traditional method that always used two nominally identical substrate elements (working electrodes). The parameters used for the ANN were derived from conventional measures of electrochemical noise data using standard deviation values and the noise resistance parameter. Additionally two other parameters using the sum of current density (coulomb count method) and a ratio index were used to give five input values for the ANN. The outputs of the ANN gave five levels of corrosion activity of zinc based coatings ranging from “A” low corrosion rate through to “E” which indicated very active corrosion.

The ANN approach appears to be very promising in taking numerous input parameters that all vary apparently independently and producing an output that can be interpreted by non-expert [26], or even subsequent software operations. This could then form part of an integrated condition monitoring system applied to engineering structures or systems in service.

4. Proposed research
The project aims to identify reliable electrochemical indicators of localised corrosion onset and propagation stages. A subsidiary aim of the project, building on the initial findings, is the production of a condition monitoring tool in conjunction with an instrument manufacturer. The tool would be based on an Artificial Neural Network that can identify:

- the likelihood of localised corrosion occurring
- the stages of localised corrosion and
- lifetime predictions.

Developments from this aspect of the project could produce a viable design for a condition monitoring probe suitable for industrial applications.

The likelihood of localised corrosion or pitting occurring is one of the most useful pieces of information that could be obtained from data sets. The ANN will recognise trends in the data or environmental factors that correspond to the signature of pitting or localised corrosion. Conditions associated with this behaviour such as solution concentration, temperature, rate of change of potential and current will be used as inputs for the ANN model. Klapper [27], showed current transients in the region of tens of nA over a period of approximately 0.4 mins. Modern ECN instruments can record date easily at this resolution which should enable pitting events to be easily identified. The initial aim above of predicting that a localised corrosion process is imminent would be a novel development in the use of ANN with corrosion systems.

If the stage above is successful this could lead on to areas such as identifying the stages of localised corrosion such as re-passivation or corrosion rate which could eventually lead to lifetime predictions.
Studies using 304SS in different concentrations of NaCl [28] showed linear [log] relationships for pitting potential (E_{pit}) V NaCl concentration. Increases in current without oxygen evolution denote the breakdown of the passive layer locally and nucleation of pitting. Similar but inverse relationship is demonstrated in this paper when inhibitor concentration in 0.5M NaCl V E_{pit} is plotted. Other workers [29], have shown these type of relationships hold for systems using aluminium in chloride solutions and have gone on to use the data in different analytical models such as damage function analysis (DFA) and Monte Carlo simulations. It should be possible to use these type of relationships as inputs for the ANN which could then be used ultimately to establish the resistance of new materials to pitting.

5. Experimental methodology

The following methodology will be used:
- Electrochemical noise data will be obtained from systems prone to localised corrosion using techniques previously developed by the author.
- Data will also be obtained using electrochemical techniques such as polarisation scans and linear polarisation resistance and comparison made with the EN data.
- Analysis of the EN data will be carried out in the time domain and the effects of localised corrosion mechanisms on data distribution will be fully investigated.
- Values from the electrochemical tests at various stages of localised corrosion will be compared and used as inputs for an ANN. In conjunction with the instrument manufacturer ACM, the ANN will be trained on the data to provide outputs to predict initiation stage, propagation and time to failure for different systems.
- The results of the ANN models will be compared to experimental and test sample results.

5.1 Novelty

The combination of ANN and data obtained from electrochemical noise to predict localised corrosion would be a novel development in the use of ANN and ECN technology areas. Condition monitoring systems and analysis by ANN to produce an output that can be used by a non-expert or as an input for another system will be a novel achievement in corrosion monitoring. It is the non-intrusive nature of the technique that means it can be used for extensive periods, continuously or intermittently, to obtain data without interfering with the system dynamics. This makes it an ideal technique for both experimental work in the laboratory and long term use in industrial applications.

The adaption of the original “Bridge Method” for obtaining ECN data into a more versatile set-up that can be used on site has been a long term aim of work in this area. It is intended that initial experimental data will be obtained using the traditional method in the laboratory. This will then be used to corroborate data from the alternative techniques before they are tested on external or real life systems. The two alternative arrangements for obtaining ECN data are the Single Substrate technique (SS) and the NOCS techniques (No Connection to the Substrate). Both have been proven empirically on coated and bare metal systems but to date they have not been used for obtaining data on localised corrosion systems. The use of these techniques to obtain localised corrosion data would, if successful, be another novel area of application for this technology and could lead to a better understanding of the fundamental mechanisms of localised corrosion and the techniques themselves. The totally non-intrusive nature of the monitoring technique will make it an attractive component of a condition monitoring system for new plant or systems under development.

5.2 Specific Objectives to achieve aims

The proposed project has following the specific objectives:
- Modification of standard test equipment to allow electrochemical measurements to be made. This will include the fabrication of test cells which can be attached to standard test samples to provide an environment that produces localised corrosion.
- Production of sound data sets for each stage of the corrosion process for analysis and generation of input parameters for ANN models. Data will be corroborated using additional electrochemical techniques and physical examination of samples.
- Production of ANN models which can be used within Instrument software to assess and predict corrosion behaviour under localised conditions.

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