

## Study on Iron Bacteria Induced Corrosion Based on Electrochemical Noise and RBF Neural Network

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**Abstract:** In this study, a study on iron bacteria induced corrosion based on Electrochemical Noise (EN) and Radial Basis Function (RBF) neural network is presented. Through the iron bacteria's corrosion compared test on C304 stainless steel, we use time domain analysis, frequency domain analysis and RBF neural network to analysis the EN data received by electrochemical workstation. Compared the results obtained by the three methods, we can conclude that the RBF neural network can recognized the iron bacteria induced corrosion types, with more advance than the traditional analysis methods.

**Keywords:** Frequency-domain analysis, iron bacteria, radial basis function, stainless steel c304, time-domain analysis

### INTRODUCTION

Metal corrosion is a status occurred as a result of environment's effect of metallic materials, then turned into a new phase or damaged. Electrochemical corrosion is the most common type of corrosion and the hot topics in the microbiologically influenced corrosion of metal corrosion (Victoria, 2001; Eimutis *et al.*, 2007). Microbiological Influenced Corrosion (MIC) is the corrosion caused by microbe, or effected by microbial corrosion, as an electrochemical corrosion (Fan, 2006). In modern industrial water, there are many types of bacteria causing microbial corrosion, sulfate-reducing bacteria and iron bacteria are two types of these bacteria which have the greatest effect (Chang *et al.*, 2007; Zhu and Yahui, 2004).

Metal corrosion often causes huge economic loss. There are many reasons that cause metal corrosion and MIC can not be ignored. 20% of the loss is caused by MIC, the economical loss can achieve  $3 \times 10^8 - 5 \times 10^8$  \$. So, how to identify the corrosion type fast and accurate is very important.

Up to now, research on this filed often use Time-domain analysis, Frequency-domain analysis and Power Spectral Density (PSD) as analysis method. Time domain analysis refers to the standard of the current noise, pitting index and noise resistance to analysis corrosion process and corrosion degree. Frequency domain analysis refers to use treated-data transfer to frequency domain and then based on slope of PSD to judge the corrosion type. But there are some short comes, time domain analysis is suit for monitoring and noise resistance relies on the sampling time and sampling frequency, in order to get more information, we must have a frequency big enough. Frequency

domain analysis is very difficult to explain the non-stable system (Gao, 2007). The frequency of PSD has no relation to the corrosion type, only have relation to the transient wave shape. By contrast, pattern recognition just can make up for these short-comes and can make speed and accuracy analysis, on the other hand, it applies to the system that have large database. RBF neural network, one method of the pattern recognition, is very popular, due to its huge database and the speed of handle.

In this study, through the study on iron bacteria's induced corrosion based on EN (Electrochemical Noise) and RBF (Radial Basic Function), we use these three methods (Time-domain analysis, Frequency-domain analysis and Radial basis function neural network) to analyzed corrosion types of iron bacteria on C304 stainless steel (Sun, 2008). In the experiment, the electrochemical noise data was received from the open state with no plus signal can reflect the essence of corrosion system state.

### MATERIALS AND EQUIPMENT

**Bacteria source:** In this experiment, Iron Bacteria are placed in the biochemical incubator which was taken from Songhua River and be enriched and purified.

**Chemical reagents:** We use API medium (its ingredient is shown in Table 1) as the experimental medium, C304 stainless steel (chemical composition is shown in Table 2) as the experimental materials.

**Experimental containers:** Grinding jars: 300 mL; Beaker: 1000 mL; Beaker: 50 mL.

Table 1: The composition of the medium

Molecular formula	Content/g/L
MgSO <sub>4</sub> ·7H <sub>2</sub> O	0.5 g
(NH <sub>4</sub> ) <sub>2</sub> SO <sub>4</sub>	0.5 g
K <sub>2</sub> HPO <sub>4</sub> ·3H <sub>2</sub> O	0.5 g
CaCl <sub>2</sub>	0.2 g
NaNO <sub>3</sub>	0.5 g
FeC <sub>6</sub> H <sub>5</sub> O <sub>7</sub> ·NH <sub>4</sub> OH	10.0 g

Table 2: The chemical composition and the proportion of 304 stainless steel

Element	C	Si	Mn	Cr	Ni	Mo	Fe
Wt%	0.07	0.48	1.55	18.5	9.35	-	Bal

**Equipment:** CHI660C Electrochemical Workstation; Digital display constant temperature water bath; Stainless steel pressure steam sterilizer; Clean bench; Biochemical incubator.

**Experimental system:** Under aerobic conditions, each of the two experimental test of C304 stainless steel was wetted in culture solution adding iron bacteria and without adding iron bacteria, cultured in the incubator in constant temperature (29±°C). Training period is 23 days. If the grinding jars of red-brown or black of brown disappears and the formation of precipitation, that is positive. Experimental materials for 50×25×2 mm, 2.205 duplex stainless steel sheets. We use CHI660C electrochemical Analyzer workstation to measurement the noise currents and the noise potential. The conical bottle was placed in the constant temperature (30°C) water bath. Experiments use three electrode systems, working area is 1cm<sup>2</sup>.

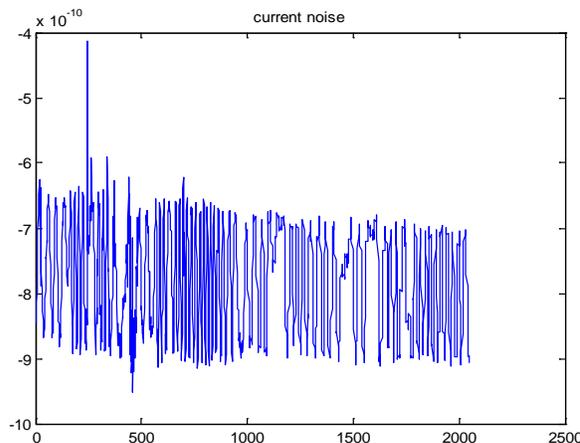
Measurement use two identical dual phase stainless steel electrode and a reference electrode composition, reference electrode is formed by extremely Saturated Calomel (SCE), using electrochemical noise modules of CHI electrochemical analyzer workstation, sampling interval is 1s, measurement time is 2048s, standing time is 30 min.

**Methods:**

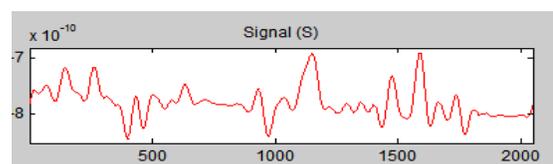
**De-noise analyses:** On the experimental data using db3 in the MATLAB 2010a Wavelet packet as noise signal, decomposition is 5 levels, de-noise and save (Hou *et al.*, 2007; Aldrich *et al.*, 2006). Figure 1 showed the original electrochemical noise signal and the electrochemical noise signal after De-noise when stainless steel immersed in medium containing Fe for 5 days.

**Time domain analysis:** Time-domain analysis includes the following parameters (Victoria, 2001):

Current noise standard deviation ( $\sigma_I$ ): generally,  $\sigma_I$  is proportion to the rate of corrosion.



(a) Before De-noise



(b) After De-noise

Fig.1: Electrochemical noise when stainless steel immersed in medium containing Fe for 5 days

$$\text{Var} = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 \tag{1}$$

$$\sigma = \sqrt{\text{Var}} \tag{2}$$

where,

$n$  = Data capacity

$x_i$  = Data sample sequence

$\bar{x}$  = Sample mean

Pitting index ( $P_X$ ): defined as  $\sigma_I$  and the noise current RMS ( $I_{RMS}$ ) ratio, the ratio close to 1, that is pitting, near 0 considered uniform corrosion:

$$I_{RMS} = \sqrt{\frac{1}{n} \sum_{i=1}^n x_i^2} \tag{3}$$

$$P_X = \sigma_I / I_{RMS} \tag{4}$$

Chen J F and others 'studies have shown that when close to 1, that show pitting corrosion, between 0.1 and 1 is localized corrosion occurred, when close to 0, uniform corrosion or passivity. However, due to the currents 'slow drift around the zero point, although is even uniform corrosion, the value of  $P_X$  is 1 (Chang *et al.*, 2007; Aruliah *et al.*, 2007).

Noise resistance ( $R_n$ ): defined as ratio of the current noising standards and the voltage noising variance and is a direct measurement of uniform corrosion.

$$R_n = \sigma_v / \sigma_I \quad (5)$$

$R_n$  and  $R_p$  received from polarization method have a good correlation, both is the direct measurement of uniform corrosion rate (Ilhan-Sungur and Coptic, 2010).

**Frequency domain analyses:** Currently, the research of electrochemical noise signals are the analysis of current or potential signals which de-noised and removed DC by fast Fourier transform or by maximum entropy method converted to the Power Spectral Density (PSD) (Stott and John, 2010; Robert and Robert, 2003). PSD function as followed:

$$S(\omega) = \lim_{T \rightarrow \infty} \frac{1}{T} \left| \int_0^{+\infty} x(t) e^{-j\omega t} dt \right|^2 \quad (6)$$

where,

$x(t)$  = Time domain function of current or potential

$T$  = Measurement cycle

$\omega$  = Frequency

### RBF NEURAL NETWORK

Methods of statistical analysis does not require expensive equipment and sophisticated analytic procedures, when used for corrosion monitoring, a quick, easy, cheap method can get qualitative or semi-quantitative conclusion, so in the massive corrosion monitoring and in the field test, it has a wide range of applications (Xu *et al.*, 2008; Kova and Leban, 2007).

Due to a high degree of complexity and nonlinear relationship between pattern samples, classification is not easy (Mansfeld *et al.*, 2002). Artificial neural networks will reflect the inherent laws implied in the network structure and parameters of neural networks, artificial neural networks gradually became a common method for solving the problem of pattern classification.

Activate function can often be expressed for:

$$R = (\|dist\|) = e^{-\|dist\|^2} \quad (7)$$

In radial basis function neural network, we often use Gaussian function as the radial basis function, the activated function can be expressed as followed:

$$R(x_p - c_i) = \exp\left(-\frac{1}{2\sigma^2} \|x_p - c_i\|^2\right) \quad (8)$$

where,

$\|x_p - c_i\|$  = European norm

$C$  = Center of the Gaussian function

$\Sigma$  = Variance of the Gaussian function

Output of radial basis function neural network structure can be received:

$$y_i = \sum_{j=1}^h w_{ij} \exp\left(-\frac{1}{2\sigma^2} \|x_p - c_i\|^2\right) \quad (9)$$

$x_p = (x_1^p, x_2^p, \dots, x_m^p)^T$  -the Pth input samples,  $p = 1, 2, \dots, p$  -Represents the number of samples,  $c^i$  -The center networks hidden layer node,  $w_{ij}$  -Connection to a hidden layer to output layer weights,  $i = 1, 2, \dots, h$  - Number of hidden layer node,  $y_j$  -the sample output of the network node that corresponds to the actual output.

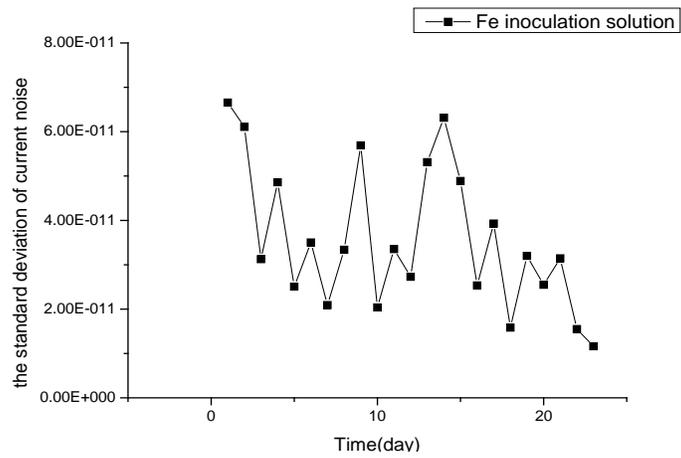
If  $d$  is the desired output of the sample, then the variance basis functions can be expressed as

$$\sigma = \frac{1}{p} \sum_j^m \|d_j - y_j c_i\|^2 \quad (10)$$

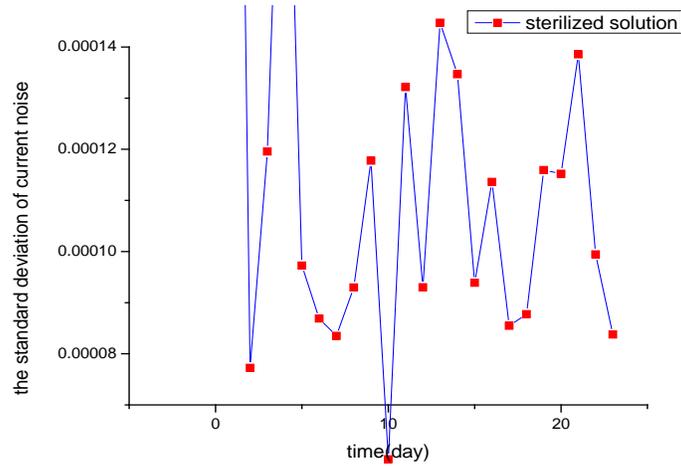
## RESULTS AND DISCUSSION

**Results of time-domain analysis:** In the bacterium medium, as time increase, corrosion rate increase and the standard of the current noise drop. The 2nd, 8th and 14th day achieved local maximum value, but less than the former, it shows that metabolism rate slows. In Fig. 4, Noise resistance inversely with corrosion rate, from the beginning, due to the electrode surface have a layer of passivity film, the resistance is large, corrosion rate is small. Along with the increase of the training time, noise resistance decrease gradually, in the first day and 14th day, achieve maximum. In sterile medium, the overall trend is down. So, we can classify the corrosion for four type, they are passivity, induced pitting, pitting and uniform corrosion and the cut-point is the 2nd, 8th and 14th. But time domain-analysis is not suit for monitoring. The experimental result is in Fig. 2 and 3.

**Results of frequency-domain analysis:** Potential noise by Fast Fourier Transform (Fast Fourier Transform, FFT) can get potential noise Power Spectral Density (Power Spectral Density, PSD) curve. From Fig. 4, Potential noise with bacterium medium for eight days to linear fitting, the slope is less than -20db, it shows that the electrode pitting happened. Eleven days after, the

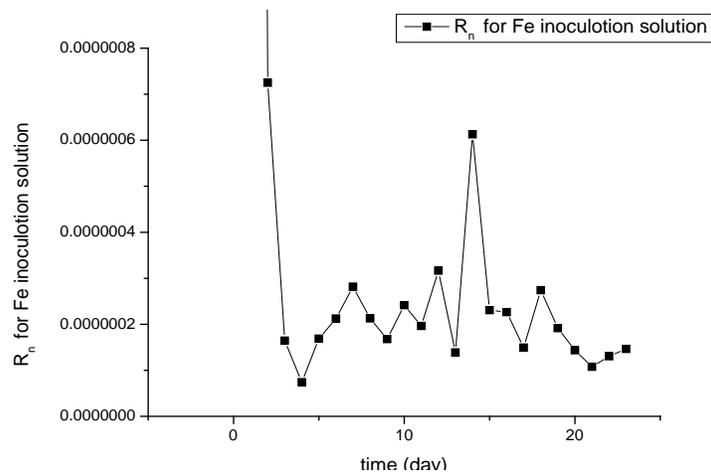


(a) The standard deviation of current noise for Fe inoculation solution

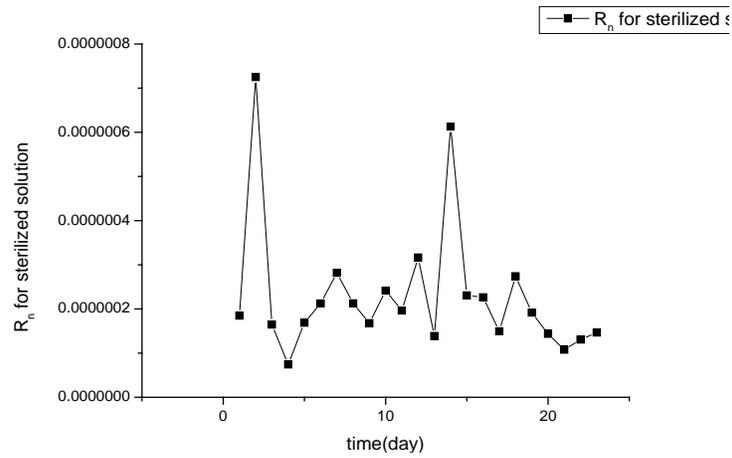


(b) The standard deviation of current noise for sterilized solution

Fig. 2: The standard deviation for solutions

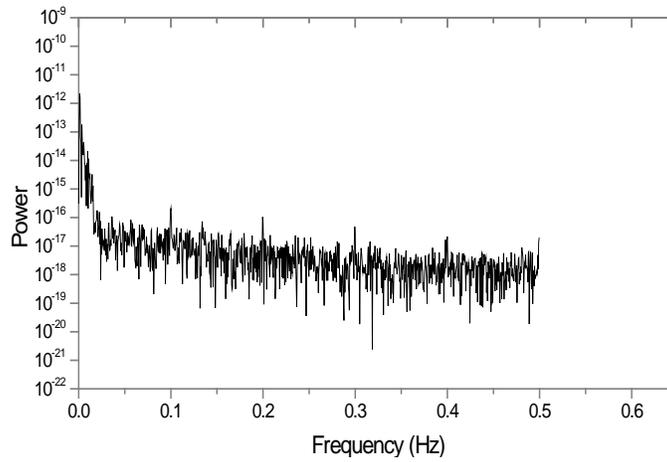


(a) Rn for Fe inoculation solution

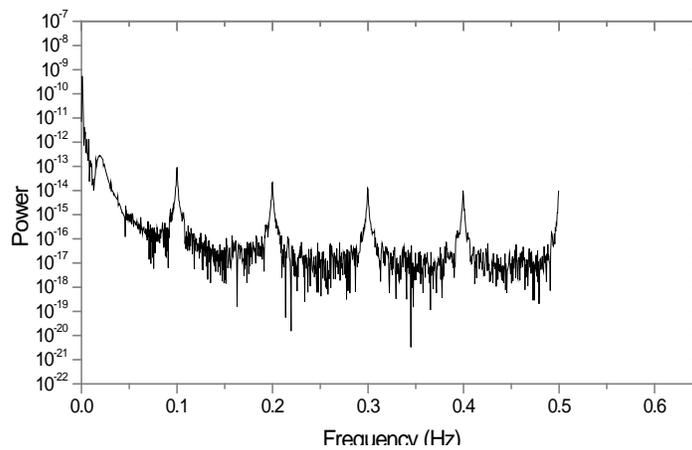


(b)  $R_n$  for sterilized solution

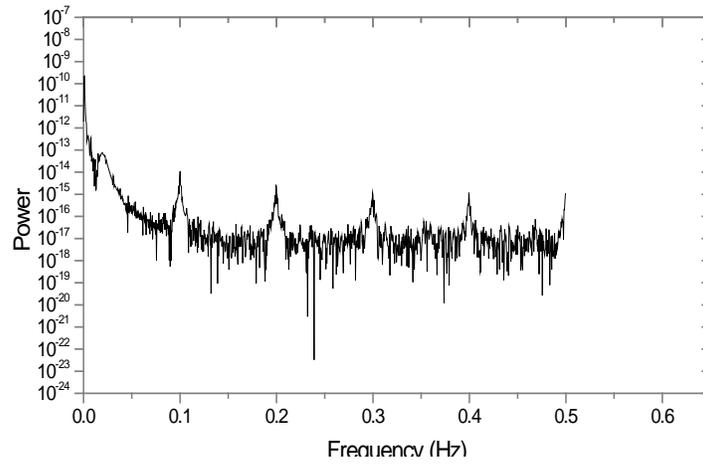
Fig.3:  $R_n$  for different solutions



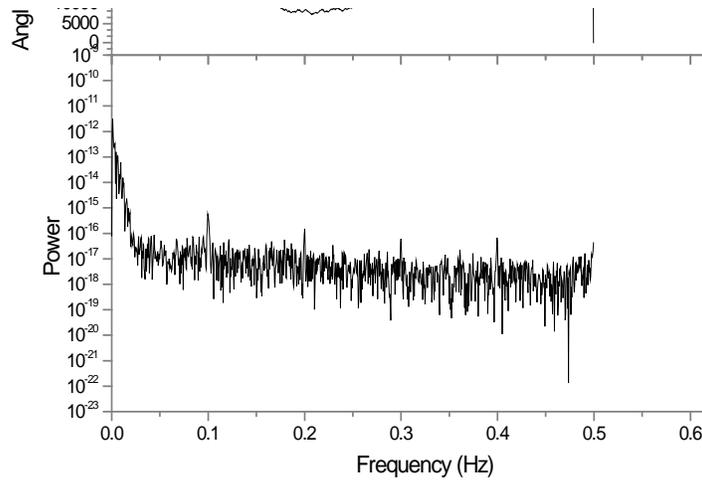
(a) The PSD curve for 2 days



(b) The PSD curve for 4 days



(c) The PSD curve for 11 days



(d) The PSD curve for 14 days

Fig. 4: The PSD curves for different time

Table 3: The recognition results of RBF

Time (day)	Corrosion type
1	I
2	I
3	II
4	II
5	III
6	III
7	III
8	III
9	IV
10	IV
11	IV
12	I

(I: Passivation; II: Induced itting; III: Pitting; IV: Uniform Corrosion)

potential PSD curve began to appear white noise, pitting corrosion points into a stable development of

corrosion points. Stainless steel for 14 days, the potential of the PSD value close to a constant in the whole noise frequency, it represents the electrode in the passivity state. We can conclusion from the above, the 11th and 14th is the cut-point.

**Results of RBF:** Take the experimental data for 12 days to corrosion type identified and the recognition results of RBF are shown in Table 3.

### CONCLUSION

According to  $P_x$  and  $R_n$ , we can classify the corrosion to four types, passivation, induced pitting, pitting and uniform corrosion. Time-domain Analysis

and Frequency-domain Analysis can get LI and  $R_p$  only and it is not exactly. In contrast, Radial Basis Function is very exact in recognition.

From the Study of Iron Bacteria's Induced Corrosion Based on EN and RBF, we can conclude that pattern recognition has advantage in pattern speed and precision accuracy and it must have a huge-space for development in Microbiological Influenced Corrosion.

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