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PERFORMANCE ANALYSIS OF CULTURALLY OPTIMIZED WAVELET LIFTING SCHEME IN CORROSION DATA FILTERING

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Abstract: The optimal design of an adaptive wavelet filter based on lifting scheme by means of evolutionary cultural algorithms is proposed, with the aim of filtering data for dynamic corrosion monitoring. First, in corrosion rate measurement through electrochemical impedance spectroscopy, the problem of uncertainty due to noise arising from underground disturbances in buried structures is stated. Then, the proposed adaptive filtering procedure is illustrated. Finally, the results of the experimental validation on two different corrosion case studies are highlighted.

Keywords: Filtering, Cultural algorithms, Wavelet transforms.

1. INTRODUCTION

Electrochemical Impedance Spectroscopy (EIS) is a reliable technique widely exploited in monitoring and analysing dynamic corrosion phenomena [1] The electrochemical dynamic response of the interface metal-electrolyte is analyzed by measuring the impedance at varying the frequency (impedance spectrum). Then, an equivalent electrical circuit, simulating the electrical behaviour of the interface, is built in order to model its physics and the kinetics of the related electrochemical reactions.

Generally, typical amplitude of EIS signals is kept very low (mV and μA), in order to consider the polarization curve of the electrochemical system under analysis to be linear [1]. In on-field applications, such as in town underground, several electrical plants are present (such as the cathodic protection itself, or cables for electrical power, phones, data transmission, television, and so on) radiating electromagnetic noise in all the buried structures. Thus, the signal-to-noise ratio (SNR) of the corrosion rate measurement may be very unfavourable. In particular, in EIS data analysis, building the equivalent electrical circuit by means of commercial software packages (such as ZView™ of Scribner Associates [2]) can become burdensome also for a skilled operator. In any case, the noise on the measured spectra generates unacceptable uncertainty in the corrosion rate measurement.

Wavelet transforms showed to be a powerful tool for filtering noisy data. Filters capable of adapting their characteristics to the specific noise, signal to be filtered, and the detail level, automatically have been developed successfully [3]. In their design, specific functions with several parameters have to be determined and optimised. With this aim, evolutionary techniques of artificial intelligence, such as Genetic Algorithms (GA), were applied [4]-[5]. However, in other applications of soft computing , GA proved to give rise to problems of inefficiency and inaccuracy [6]. Conversely, Cultural Algorithms (CA), proved to be capable of better performance, especially in multidimensional nonlinear problems of constrained optimization [7]-[14], such as in the case of designing an adaptive wavelet-based filter for EIS data [15].

In this paper, an adaptive filter, based on wavelet transforms and designed by means of CAs, is proposed and on-field tested in determining the corrosion rate of buried pipelines under severe conditions of electromagnetic noise. In particular, in Section II, the problem of inaccuracy of the corrosion rate in presence of noise is highlighted. In Section III, the basic ideas and the proposed digital filter design are shown. Finally, in Section IV, the experimental results, achieved in the application of the proposed filter to actual cases of buried pipelines monitoring via EIS, are discussed.

2. THE PROBLEM

The uncertainty on EIS spectra data, arising from noise superimposed to the electrical signals of measure, can affect significantly the estimate of the R_p and then the corrosion rate v_{cor}:

$$\mathbf{v_{cor}} = \frac{\mathbf{K \cdot E_W}}{\mathbf{d \cdot A}} \cdot \frac{\mathbf{b_a \cdot b_c}}{\mathbf{2.3 \cdot (b_a + b_c)}} \cdot \frac{\mathbf{1}}{\mathbf{R_p}} \tag{1}$$

where K is a constant related to measurement units, E_w is the equivalent weight in grams/equivalent, d is the density in g/cm^3, A is the sample's area in cm^2, and b_a and b_c are the anodic and cathodic Beta Tafel constants, respectively, in Volt by decade.

As an example, in Fig. 1, a simple ideal equivalent circuit (up), modelling corrosion phenomena of a coated pipe, and the related Nyquist diagram (bottom) are shown.

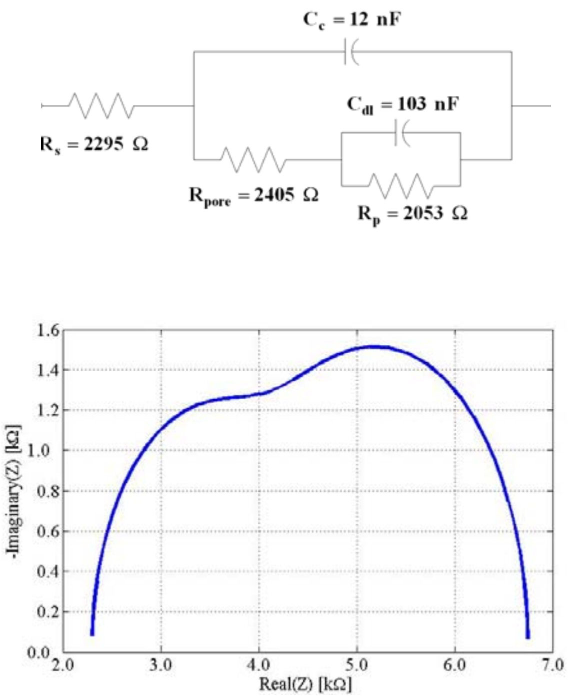

Fig.1: EIS model circuit (up) and related Nyquist diagram (bottom) for a coated pipe corrosion.

Impedance data were corrupted by additive white Gaussian noise having standard deviation σ. The resulting noisy data were fitted by means of ZView™ [2], by using the following initial values of the circuital components: R_p=R_{pore}=R_s =100 Ω, and C_{dl} =C_c =1 nF. The maximum iterations number was fixed at 100, such as suggested in the software reference guide [2].

The obtained simulation results are shown in Tab. I: in particular, the percentage standard deviation of the noise added to the impedance data, the reference value of R_p and its ZView™ estimate R_p*, the percentage relative errors on the estimate of R_p (ε_{Rp}) and of the corrosion rate v_{cor} (ε_{Vcor}), respectively, are reported. Results highlight how the estimation error increases according to the noise amount considerably, pointing out the actual need for a suitable filtering stage.

3. THE PROPOSED APPROACH

In the following, (*i*) the *basic ideas,* and (*ii*) the *proposal* of the developed adaptive filtering approach are illustrated.

Tab.I: Effects of the noise on the corrosion rate measurement.

σ (%)	Rp [Ω]	Rp* [Ω]	ε_{Rp} (%)	ε_{Vcor} (%)
0	2053	2053	0.0	0.0
1	2053	2054	0.1	0.1
5	2053	1944	5.3	5.6
10	2053	1733	15.6	18.5
15	2053	1715	16.5	19.7
20	2053	1599	28.4	22.1
25	2053	1079	47.4	90.2

3.1. *The Basic Ideas*

One way to implement a wavelet filter is to split the signal spectrum in two parts, a low-pass and a high-pass part. The high-pass part contains the signal details of interest. However, the low-pass part still contains some details and therefore it can be split again and again, until the desired number of bands is achieved. In this way, an *iterated filter bank* is obtained. Usually, the number of bands is limited by the available amount of data or computation power. The advantage of this procedure is that only two filters have to be designed, but a severe limitation is that the filter structure is fixed and, thus, can not handle sudden changes in the input signal. In EIS data filtering, however, it is desirable to have a filter bank that somehow determines how to shape itself according to the local properties of the signal. Thus, so-called *adaptive wavelets* are exploited, that is the wavelet transform is not based on filter bank iteration; but different filter banks have to be used at each step, selected by the designer according to the specific filtering exigencies in the current step.

In the middle of the nineties, a new approach to the wavelet analysis was introduced: the lifting scheme [17]. The lifting scheme is an algorithmic rearrangement to compute wavelet transform having some important advantages with respect to classical approach [16], all calculations are carried out: (i) without any auxiliary memory location, by saving memory strongly, and (ii) by reducing the floating point operations to calculate approximated and detailed parts. Thanks to the lifting scheme the implementation of the complex wavelet algorithms on poor resource system, such as low-cost microcontroller device, is possible. Moreover, the lifting scheme allows all the design step to be carried out in the time domain, by avoiding the use of Fourier analysis.

In adaptive filter design, the optimal configuration of the wavelet filter capable of minimizing the filtering error is a complex problem of multi-dimensional constrained optimization, as shown in [5]. One way to solve this kind of problems is to use evolutionary techniques, such as genetic algorithms [4]-[5], that confirmed satisfying capabilities of scanning large solution spaces. GAs exploit mainly [6]: (i) mutation, (ii) combination, and (iii) natural selection. In mutation, current configurations are altered randomly in order to generate new potential solutions. In combination, the genetic patrimony of two or more individuals are pooled (*crossover*) in order to obtain new filter configurations to be assessed. In natural selection, most promising filter configurations are selected by means of a suitable function (*fitness*), in order to transmit their genetic patrimony on best search paths to next generation of potential solutions (*elite count*).

However, the GAs proved to give rise to an intrinsic resource waste [6]. The state of the art of evolutionary techniques is based on cultural algorithms (CA); recent works [11]-[18] have shown as they result more accurate and efficient than GAs. Cultural mechanism adds further functions to the genetic evolutionary process in order to identify best search paths [9], [13]-[14]. An *accept* function select best individuals after a first genetic evolution. Their characteristics upgrade the knowledge on the best research paths situated in a suitable archive (*Belief Space),* by means of the function *update*. This archive contains also information about last best candidate solutions and a map of the search. This knowledge is transferred to new population's individuals through the *influence* function, by giving rise in this way to a cultural evolution, and avoiding resource waste of genetic evolution.

3.2. The Proposal

A wavelet transformation through a lifting scheme consists of three recursive basic steps [17]: (i) *split* the signal s_j into its odd and even components, (ii) *predict* the odd from the even samples (function *P*), *compute* the wavelet coefficients as difference between odd and predicted samples, and (iii) *update* the even component with a combination of the detail (function *U*), in order to approximate the original signal. The inverse transform is carried out simply by reversing the order of the operations and changing the signs. Wavelet coefficients are represented analytically by:

$$d_{j-1}(k) = s_j(2k+1) - \sum_m p(m) \cdot s_j(2m+2k), \qquad (2)$$

where k = 0,…,2j ; the approximation sj-1 is represented as:

$$s_{j-1}(k) = s_j(2k) + \sum_m u(m) \cdot s_j(2m+2k+1). \qquad (3)$$

In adaptive filter design, the optimal configuration expressed by *2m·j* filter's coefficients and the *j-th* threshold levels, capable of minimizing the filtering error and satisfy the following constraints [5]:

$$\sum_m p(m) = 1 \ , \ \sum_m u(m) = 1/2 \qquad (4)$$

simultaneously, have to be found.

The solution of the above problem of multi-dimensional constrained optimization is based on five steps (Fig. 2):

1. An initial population (*Initial Pop.*) is generated randomly. Each individual is composed by chromosomes: i.e., sets of filter coefficients consisting in the parameters of the *P* and *U* operators, and the threshold levels, each one different for every wavelet decomposition.
2. The filter coefficients of each individual are used in order to decompose the noisy signal (a case of the starting design requirements: classes of signal *{s}* and noise *{n}*) trough the lifting scheme (*LSWT*). Thresholding (*Thres.*) is then applied to the detail coefficients. Wavelet reconstruction (*ILSWT*) is computed by using the original approximation samples and the modified detail coefficients of the *N* levels, in order to obtain the de-noised signal.
3. For each filter coefficient set (a population individual), the fitness function (*F*), e.g. the RMS error between the original noiseless and the filtered signal, is evaluated.
4. By scoring the fitness function, the best individuals are selected (*Select*) and the entire population evolves (*Evolution*) in order to obtain the new generation, by giving rise in this way to the genetic evolution.
5. Steps 2 to 4 are repeated for a fixed number of times; then, a cultural mechanism select the best individuals (*Accept*) in order to *update* the knowledge and *influence* the next generation.

Such a process is repeated from 2 to 5, until a stop condition on the desired quality of the solution (or a timeout) is achieved. The best individual of the last population, i.e. characterized by the best fitness, holds the optimal parameter combination of *P* and *U* operators and of the threshold levels, representing the solution of the filtering design problem.

4. EXPERIMENTAL RESULTS

The proposed method was validated experimentally on two different corrosion case studies. In the following, (i) the *experimental setup*, (ii) the *test conditions,* and (iii) the *experimental results* are highlighted.

4.1. Experimental Setup

Experimental measurements were carried out at the COLUMBIA GAS test facility in Sugar Grove outside of Lancaster, OH (USA) [19]. The equipment used for field impedance measurements includes: a Frequency Response Analyzer (Model TF2000, Voltech) connected to an IBM PC, a Potentiostat/ Galvanostat (Model 363, EG&G Instruments), electrode connectors for working, counter and reference electrodes (copper-copper sulfate reference electrode Model 8B, TINKER & RASOR), and an AC power connector.

4.2. Test Conditions

In the first case study, a gas pipe without external coating and defects, buried in soak soil owing to raining water is considered, measurements were performed in the range of frequencies from 1 Hz to 100 kHz. In the second case study, the gas pipe was coated but with some holydays, also buried in soak soil owing to raining water, the frequency range was selected from 0.1 Hz to 100 kHz. The Nyquist diagram of the measured impedance data normalized respect to the Potentiostat Resistance (R_{pot}) are reported in Fig.3 (left: uncoated pipe of case study 1, and right: coated pipe of case study 2).

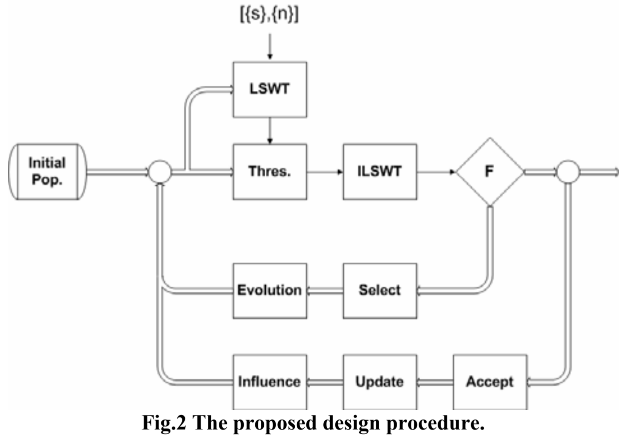

Fig.2 The proposed design procedure.

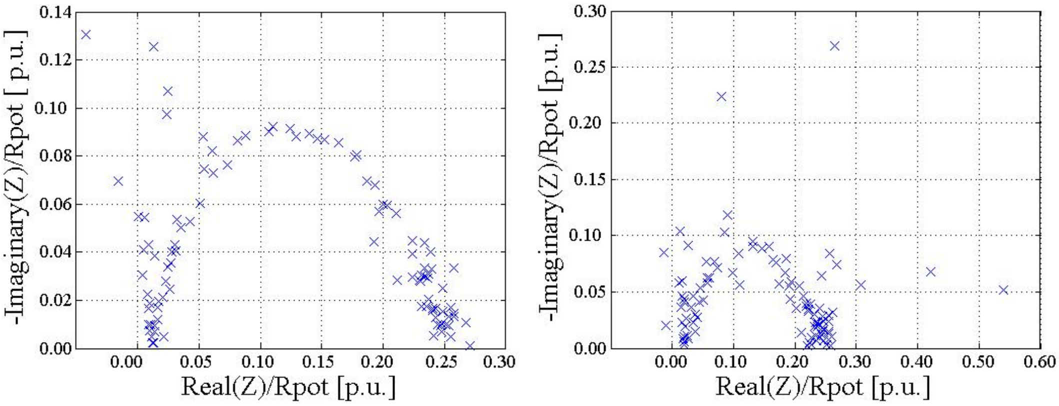

Fig.3: Nyquist diagrams of the impedance data of the case study 1 (left: uncoated pipe) and 2 (right: coated pipe), normalized respect to Potentiostat resistance.

The proposed procedure is situated in the field of the project [19]. The project is aimed at studying techniques for the experimental characterization of dynamic parameters of electrochemical phenomena in the corrosion of metallic materials, by digital measurement procedures suitable to be implemented on low-cost micro-devices. Thus, the filtering procedure and the subsequently data analysis are thought in a stand-alone system, without any external operator intervention.

The reference R_p values were evaluated by fitting the depressed circular arc of the experimental data by means of ZView™ manually by means of the circuit shown in Fig.4, since the main information concerning the corrosion rate is related to the arc. In particular, the initial values of the equivalent circuital components were changed until a satisfying agreement between experimental and fitted data was achieved. The maximum iterations number of ZView™ was fixed at 100.

The obtained fitted data were used to set-up the ZView™ to simulate an automatic fitting procedure in a stand-alone system. The initial circuital components were chosen as follow: $R_p = R_s = 1\ \Omega$, CPE-α = 0.5, CPE-A = 0.1 Ω/s^{α} , in this way the ZView™ was able to fit exactly the given data.

Given the above software configuration, the experimental EIS data were again analyzed by the ZView™.

The same parameters were used to fit the data filtered by means of the proposed procedure. In particular for the CA-based wavelet filter design, 3 decomposition levels were chosen; for each level, 3 parameters (1 for predict, 1 for update, and 1 for the threshold) are needed. Thus, each individual is composed by 9 chromosomes. The CA was configured according to literature [8]-[15]: populations size of 500 individuals, GA generations 50, CA generations 20, elite count 1, crossover fraction 60%, and mutation fraction 10 %.

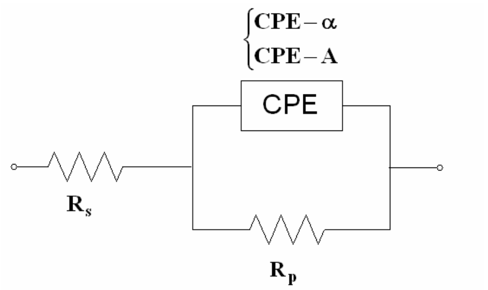

Fig.4: Fitting circuit.

4.3. Experimental Results

Experimental results are reported in Tab. II, in particular the reference value of R_p and its ZView™ automatic estimate R_p*, the percentage relative errors on the estimate of R_p (ε_{Rp}) and of the corrosion rate v_{cor} (ε_{Vcor}), for the two above mentioned case study making use of the raw experimental data and of the CA filtered data.

The results show that the estimate of R_p, in an automatic procedure, without a filtering stage introduce significant errors. In the same table is highlighted that the CA filter allow to reduce the estimate error.

5. CONCLUSIONS

A procedure for the optimal design of adaptive wavelet filters based on lifting scheme by means of CA was proposed. The proposed approach highlighted its effectiveness in practical experimental applications of EIS, in particular on two different corrosion case studies.

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Tab.II: Experimental results.

		R_p/R_{pot} [p.u.]	R_p^*/R_{pot} [p.u.]	ε_{Rp} (%)	ε_{Vcor} (%)
Case 1	Unfiltered Data	0.22	0.19	14	16
	CA Filtered Data	0.22	0.22	1	1
Case 2	Unfiltered Data	0.22	0.25	15	13
	CA Filtered Data	0.22	0.21	6	7

REFERENCES

[1] E. Barsoukov and J. Ross Macdonald, "*Impedance Spectroscopy : Theory, Experiment, and Applications", 2005.*

[2] http://www.scribner.com

[3] I. Selesnick, "The Slantlet Transform" IEEE Transactions on Signal Processing, Vol. 47, N° 5, May 1999.

[4] Takehisa, "*Adaptive Wavelet Transform for Lossless Compression using Genetic Algorithm*", 2000 Genetic and Evolutionary Computation Conference.

[5] E. Jones, P. Runkle, "*Genetic Algorithm Wavelet Design for Signal Classification*", IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 23, no. 8, august 2001.

[6] W. Gao, "Comparison study of genetic algorithm and evolutionary programming", Proc. of the Third Int. Conf. on Machine Learning and Cybernetics, Shangai, 26-29 August, 2004, pp. 204-209.

[7] G. B. Fogel, D. B. Fogel, "*Continuous evolutionary programming: analysis and experiments*", Cybernetics and Systems, Vol. 26, 1995, pp. 79-90.

[8] R. G. Reynolds, W. Sverdlik, "Problem solving using cultural algorithms" Proc. of the First IEEE Conf. on Evolutionary Computation, 27-29 June 1994, pp. 645 – 650.

[9] J.G. Digalakis, K.G. Margaritis, "*A multipopulation cultural algorithm for the electrical generator scheduling problem*", Mathematics and Computers in Simulation 2002, Vol. 60, pp. 293-301.

[10] M. Stenberg, R. G. Reynolds, "*Using cultural algorithms to support re-engineering of rule-based expert systems in dynamic performance environments: a case study in fraud detection*", IEEE Trans. on Evolutionary Computation, Vol.1 ,No. 4, November 1997, pp 225-243

[11] N. Rychtyckyj, R. G. Reynolds, "Knowledge base maintenance using cultural algorithms: application to the DLMS manufacturing process planning system at Ford Motor Company", IEEE Proc. Congress on Evolutionary Computation, Honolulu, USA, May 12-17 2002, pp 855-860.

[12] S. Saleem, R. G. Reynolds, "*The impact of environmental dynamics on cultural emergence*". Festschrift, in honor of John Holland, Oxford University Press, 2003, pp.1-10.

[13] P. Arpaia, G. Lucariello, A. Zanesco "*Automatic fault isolation by cultural algorithms with differencial influence*", IEEE Trans. on Instrum. and Meas. 2005 – Submitted.

[14] P. Arpaia, G. Lucariello, A. Zanesco, "Multi-agent remote predictive diagnosis of dangerous good transports", IMTC 2005 – Instrumentation and Measurement Technology Conference Ottawa, Canada, 17-19 May 2005.

[15] P. Arpaia, C. Romanucci, A. Zanesco, "Optimal design of wavelet filters based on lifting scheme by means of cultural algorithms", IMTC 2006 - Instrumentation and Measurement Technology Conference Sorrento, 2006.

[16] Jer Min Jou. Yeu-Horng Shiau. and Chin-Chi Liu. "Efficient VLSI architectures for the biorthogonal wavelet transform by filter bank and lifting scheme" *Circuits and Systems*, ISCAS 2001. The 2001 IEEE International Symposium on, vol. 2, pp. 529 –532, 2001.

[17] W. Sweldens "Building your own wavelets at home", In: Wavelets in Computer Graphics. ACM SIGGRAPH Course Notes, 1996.

[18] A. Cohen, I. Daubechies, and J. Feauveau. "*Bi-orthogonal bases of compactly supported wavelet.*" Comm. Pure Appl. Math., 45:485-560, 1992.

[19] P. Arpaia, M. Urquidi Macdonald, C. Romanucci, "Wavelet-based filtering of eis corrosion data optimized by cultural algorithms", CEOCOR 06, Luxemburg, May 2006.

[20] Regione Campania (L.R. N.5, 28.03.2002), "Experimental characterization of dynamical phenomena of electrolytic corrosion in metallic materials by digital measurement techniques".

[21] Regione Campania (law 598/94), "Low-invasive measurement of prothesis osseo-integration by variable-polarization impedance tomography" (in Italian), 2004.