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PERFORMANCE COMPARISON BETWEEN COMPLEX NON-LINEAR LEAST SQUARES AND GENETIC ALGORITHMS IN IMPEDANCE CIRCUIT PARAMETER ESTIMATION

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Abstract – Electric circuit parameter estimation from its impedance frequency response is becoming increasingly important due to the wide range of applications that it finds both in science and industry. This paper presents a comparison of the performance of a genetic algorithm and the complex non-linear least squares implemented in the LEVM/LEVMW software in the estimation of impedance circuit parameters. The comparison is focused on the standard deviation of the estimated values, convergence rate and execution time of each algorithm.

Keywords: genetic algorithms, complex non-linear least squares, impedance parameter estimation

1. INTRODUCTION

Electrical impedance spectroscopy has many applications ranging from corrosion analysis [1] to biomedical applications [2]. For example, it has been used to characterize sensors [3] and also glucose solutions [4]. Due to the increasing amount of applications of impedance spectroscopy (IS), there has been an effort to improve the efficiency of all the methods involved in IS which include data acquisition, electrical circuit model adaptation and circuit component values estimation.

The reference procedure for estimation of circuit component values is the complex non-linear least squares (CNLS) implemented in the LEVM/LEVMW software which is freely available [5]. However, recently other approaches have been proposed which include the use of evolutionary algorithms. An example is the use of a genetic algorithm (GA) [6] which has been successful in the estimation of circuit components from measured impedance frequency responses.

This paper is focused on the performance comparison of the LEVM/LEVMW software and a Matlab implementation of a genetic algorithm for the estimation of electric circuit parameter values. Numerical simulated impedance responses, which include measurement uncertainty, of a test circuit are used for this comparison. The standard deviation of the estimated circuit component values by both methods is analysed along with the convergence rate and the average execution time for 10000 trials.

2. IMPEDANCE CIRCUIT PARAMETER ESTIMATION

This section presents the electric circuit used to compare the performance of the genetic algorithm and the LEVM software in the estimation of the parameters of an electric circuit. The basic inner works of the genetic algorithm along with a brief explanation of the CNLS algorithm and LEVM application is presented.

2.1. Sensor equivalent circuit

The equivalent circuit used to evaluate the performance of the GA and CNLS algorithm is shown in Fig. 1. It is the equivalent circuit of a viscosity sensor based on a vibrating wire whose resonance frequency and quality factor depend on the viscosity of the liquid [7]. The R_s and L_s components take into account the impedance of the connecting wires while the *GLC* parallel is related to the wire resonance. The *G* component is a frequency dependent conductance whose impedance is $Z_G = 1/(G\omega)$.

The component values shown in Fig. 1 correspond to the sensor equivalent circuit when it is immersed in a liquid with a viscosity of 123.24 mPa.s. It has been shown that the viscosity of a liquid can be obtained from the component values of this equivalent circuit [8].

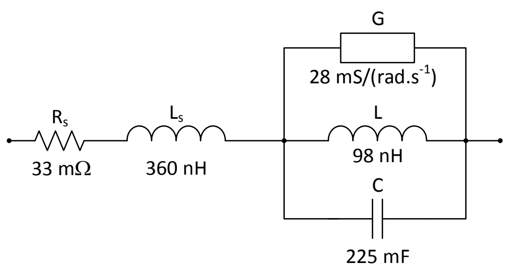

Fig. 1. Vibrating wire sensor equivalent circuit.

The measurement procedure consists on: measuring the impedance frequency response of the sensor when immersed in a liquid; estimate the component values that minimize, in a least squares sense, the error between the measured impedance and the theoretical impedance with those values; and then estimate the viscosity of the liquid [8]. The search for the component values can be performed in LEVM which implements a CNLS algorithm or, as more recently proposed, through a genetic algorithm (GA).

2.2. Genetic algorithm

A genetic algorithm is a type of evolutionary algorithm which follows the paradigm of survival of the fittest and includes population evolution operations such as reproduction and mutation. It is suitable to be used in multi-dimensional optimization problems with a large search space and that include multiple local optimum points. Under those conditions, traditional search algorithms can fail to reach the global optimum point because they can get trapped in local minima.

In the implemented genetic algorithm a population of 40 potential solutions are randomly generated. Each population individual is composed of 5 genes where the value of each gene corresponds to a component value of the circuit in Fig. 1. These values are randomly generated through a uniform distribution in the logarithmic space of the ranges shown in Table 1.

Table 1. Component search space used by GA.

Component type	Search range
R	$[10^{-3}; 10^{6}]\ \Omega$
L	$[10^{-9}; 10^{0}]$ H
C	$[10^{-9}; 10^{0}]$ F
G	$[10^{-9;}\ 10^{0}]$ S/(rad.s^{-1})

The fitness of each individual is assessed with the cost function

$$\varepsilon = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Z_m(f_i)-Z_{est}(f_i)}{Z_m(f_i)}\right|^2 \qquad (1)$$

where Z_m is the measured complex impedance at the N frequencies f_i and Z_{est} is the complex impedance estimated with the component values of each individual. The individuals are then sorted according to their fitness (lowest value of ε) and the most fit have a better chance at reproduction to pass their characteristics on to the next generation. A new generation of the population is created through reproduction and also mutation to increase diversity (the probability for reproduction is p_{cross} = 0.8 and for mutation is p_{mut} = 0.3). The fitness of this new population is again determined using (1). This process is repeated until a predefined cost function threshold is obtained or the maximum number of generations is reached. At this point a Nelder-Mead simplex algorithm is used to fine-tune the solution using as starting point the best component values returned by the genetic algorithm.

2.3. Complex non-linear least squares

To test the performance of the complex non-linear least squares, the LEVM software was used. This software implements the CNLS method which tries to minimize the error between both the real and imaginary components of the measured impedance response and the real and imaginary counterparts of the estimated impedance response.

An interface with Matlab has been developed so that the input file needed for the LEVM software can be automatically created. This file defines the initial search parameters, the maximum number of function evaluations and includes the impedance frequency response data, among other parameters. The LEVM software writes the results in a text file which is then read in Matlab for data processing.

The LEVM software includes different circuit templates which can be used. One circuit template that has a topology that fits the circuit in Fig. 1 is circuit J [9]. It includes the R_s and L_s components and two distributed elements that can be adjusted to fit the frequency dependent conductance G and the inductance L. The C component is explicitly included in circuit template J.

The LEVM fitting results are compared against the impedance frequency response of the circuit in Fig. 1. If the fitness error as defined in (1) is below a predefined threshold the CNLS is considered to have converged to the true solution.

3. NUMERICAL RESULTS

The impedance frequency response of the circuit in Fig. 1 was computed for 100 points in the range [200; 2000] Hz to include the resonance region which characterizes the *GLC* components of the equivalent circuit. To simulate measurement uncertainty, the amplitude and phase of the simulated impedance include normally distributed random errors with standard deviation of 0.08% for the impedance magnitude and 0.05º for the impedance phase. An example of the impedance magnitude is shown in Fig. 2 while the impedance phase is presented in Fig. 3.

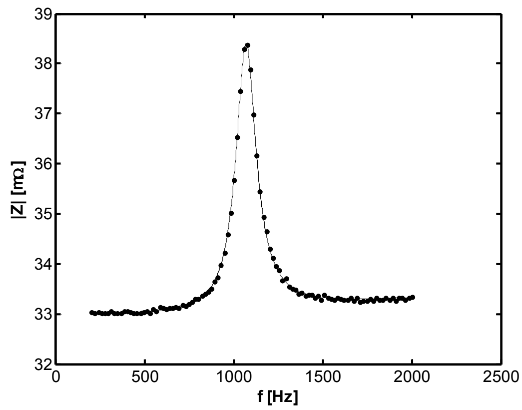

Fig. 2. Impedance magnitude frequency response of the circuit in Fig. 1. For each value, a 0.08% standard deviation uncertainty was included to simulate actual measurement conditions.

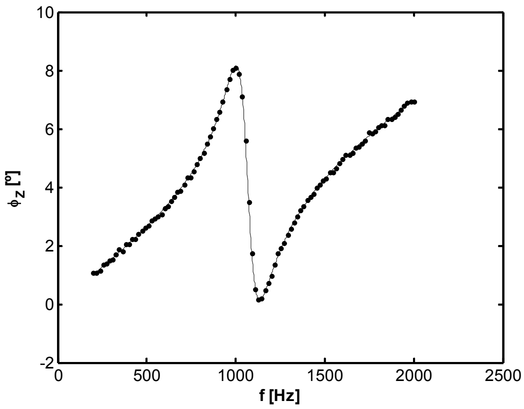

Fig. 3. Impedance phase frequency response of the circuit in Fig. 1. For each value, a 0.05º standard deviation uncertainty was included to simulate actual measurement conditions.

The genetic algorithm was applied to 10000 different realizations of the simulated impedance frequency response. The resulting component values of the runs that converged are presented in the red histograms of Fig. 4 to Fig. 8. The histogram of each component value is centred near the nominal value defined in Fig. 1.

The LEVM program was also applied to 10000 different realization of the simulated frequency response. The initial search values for each component were randomly selected considering a ±10% margin relative to the nominal values as set in Fig. 1 (*e.g.*, the initial search value of the R_s component was randomly selected in the range [29.7; 36.3] mΩ). The histograms of the resulting component values (in the cases that the algorithm converged) are shown in blue in Fig. 4 to Fig. 8.

The comparison between the histograms obtained with GA and with the LEVM program show that the genetic algorithm estimated parameters have lower standard deviation than the LEVM estimated parameters even though the search space of each component value spans several orders of magnitude while the LEVM initial search values are within 10% of the components nominal values. The average values and standard deviations of each component are listed in Table 2 for both algorithms.

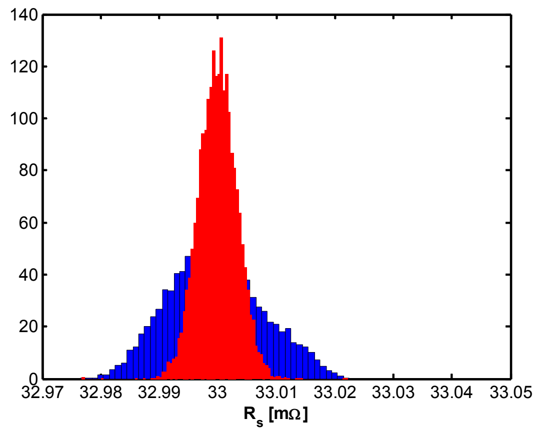

Fig. 4. Histogram of the estimated R_s value in 10000 runs by GA (red) and CNLS (blue).

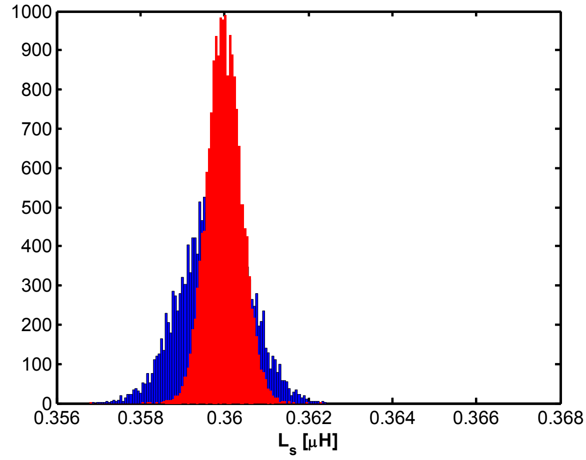

Fig. 5. Histogram of the estimated L_s value in 10000 runs by GA (red) and CNLS (blue).

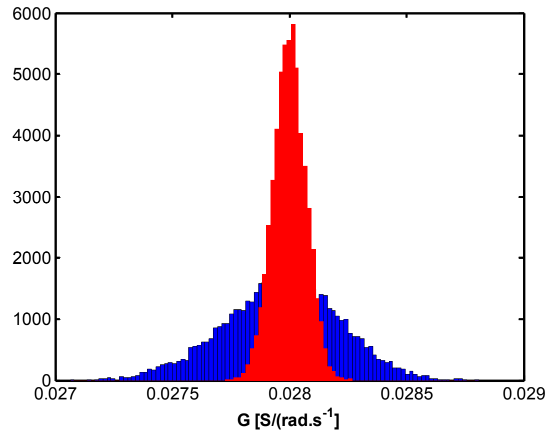

Fig. 6. Histogram of the estimated G value in 10000 runs by GA (red) and CNLS (blue).

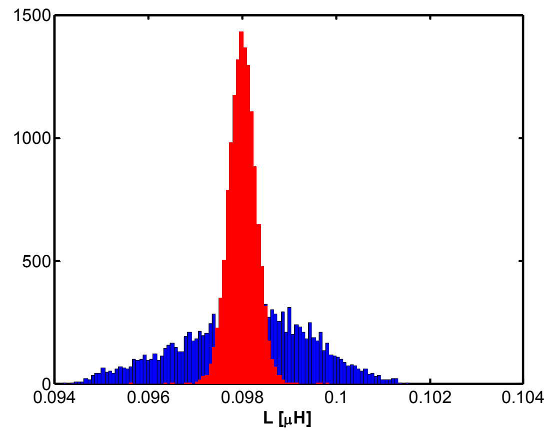

Fig. 7. Histogram of the estimated L value in 10000 runs by GA (red) and CNLS (blue).

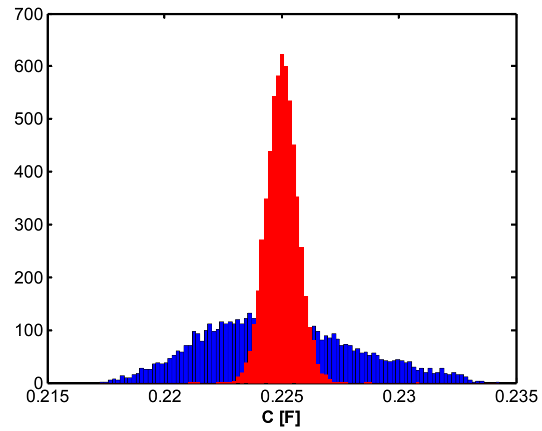

Fig. 8. Histogram of the estimated *C* value in 10000 runs by GA (red) and CNLS (blue).

The genetic algorithm converged in 9310 of the 10000 runs. To analyse the convergence performance of the LEVM software, three different cases were considered: Case 1 - initial search values within 10% of the nominal values which corresponds to the situation shown in Fig.4 to Fig. 8; Case 2 - initial search values within 20% of the nominal values; Case 3 - initial search values within 1 order of magnitude of the nominal values. The convergence rates are presented in Table 3 and show that the LEVM software has difficulties in converging when the initial search parameters are not close to the nominal values. On the other hand, GA converges most of the time even with search spaces that span several orders of magnitude – see Table 1.

Another comparison that was performed was in the execution time of each algorithm. Each GA execution takes on average 4.43 s while the LEVM took, on average, 7.53 s which included the creation of the input file, executing the algorithm and creation of the multiple output files by LEVM.

Table 3. Convergence rate for GA and CNLS.

	Convergence rate
GA	93.1%
CNLS – Case 1	90.2%
CNLS – Case 2	89.0%
CNLS – Case 3	10.0%

4. CONCLUSIONS

This paper compares the performance of a genetic algorithm and the CNLS algorithm implemented in the LEVM software for the estimation of impedance circuit parameters. The GA was shown to have lower standard deviations in the estimation of the component values of a test circuit. It was also shown that GA has a better convergence rate despite the initial search space which spans several orders of magnitude of the actual component values. The GA was also faster than LEVM but this can partially be justified by the file input/output operations needed to operate the LEVM.

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Table 2. Average and standard deviation of the component values estimated by the CNLS and GA algorithms.

	CNLS		GA	
Component	Average value	Standard Deviation	Average value	Standard Deviation
R_s [mΩ]	32.99964	0.00804	32.99999	0.00328
L_s [nH]	359.768	0.798	359.995	0.410
G [mS/(rad.s^{-1})]	27.966	0.246	28.0001	0.0705
L [nH]	98.04	1.36	97.994	0.287
C [mF]	224.92	3.18	225.016	0.661