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Development of an automated system based on the concept of evolutionary hardware to determine the optimal operating point of GMI sensors

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Abstract. The sensitivity of a magnetometer is directly associated with the sensitivity of its sensor elements. In the case of GMI sensors, this sensitivity is optimized by maximizing the variation of their impedance magnitude or phase as a function of the magnetic field to which the sample is subjected. Previous studies showed that the sensitivity of Co_{70}Fe_{5}Si_{15}B_{10} samples is most affected by four parameters: sample length, biasing magnetic field, DC level and the frequency of the excitation current. However, the search for the set of parameters that optimizes the sensitivity of the samples is usually empirical and very time consuming. Thus, this paper proposes a new optimization technique, based on the use of genetic algorithms evolving in hardware, in order to define the set of parameters responsible for maximizing the samples sensitivity.

1. Introduction

Giant Magnetoimpedance (GMI) sensors are a new family of magnetic sensors that exhibit a huge variation of their impedance when subjected to external magnetic fields. These sensors have been used in the development of high sensitivity magnetometers, aimed at measuring ultra-weak magnetic fields. In turn, the sensitivity of a magnetometer is directly associated with the sensitivity of their sensor elements. In the case of GMI samples, this sensitivity is optimized by maximizing the variation of the impedance magnitude or phase as a function of the magnetic field applied to the sample [1–2].

The sensitivity of GMI sensors is affected by a set of conditioning parameters. However, currently, there is no sufficiently general physical model capable of modeling the impedance sensitivity in function of the entire set of parameters that affected it. Thus, the search for the optimal combination of these parameters is usually empirical [3].

Recent researches indicate that GMI magnetometers based on impedance phase readings have significantly higher sensitivities than those based on impedance magnitude readings [4–6]. Consequently, this paper focus on the optimization of the phase sensitivity of GMI samples. In previous studies, experimental tests were performed with Co_{70}Fe_{5}Si_{15}B_{10} ribbon-shaped GMI samples in order to determine the set of parameters that most affects the sensitivity of the analyzed samples. The obtained results have showed that the most critical parameters are: length of the sample (l), DC level (I_{DC}) and frequency (f) of the excitation current, in addition to the biasing magnetic field (H_{pol}) [7].
The search for the set of parameters that optimizes the sensitivity of the samples is usually empirical and very time consuming. Thus, this work proposes a new optimization technique, based on the use of genetic algorithms evolving on hardware, in order to define which set of parameters is responsible for maximizing the sensitivity of the samples.

2. Automatic Optimization System

The automatic optimization system developed in this work allows defining the set of parameters \((I_{DC}, f, H_{pol})\) that leads to the maximization of the impedance phase sensitivity \((S_{phase})\) of GMI sensors with different chemical compositions and geometric shapes (length, thickness and width). The developed system is controlled by a computational model based on genetic algorithms, implemented so that the genes of the individuals of the population are represented by real numbers associated to each of the parameters that affect the sensitivity of the sensors. The equipment used in the system have their values adjusted by the genes of the individuals, so that the sensitivity corresponding to each individual can be measured experimentally. In turn, the developed GA uses the experimental measurements of the sensitivity as its fitness function, in order to estimate the aptitude of each individual.

The hardware of the system for automatic optimization of GMI samples have six main modules: LCR meter (4285A, Agilent); Current source (E3648A, Agilent); Helmholtz Coil; Polarity inverter, data acquisition board - DAQ (NI USB-6221, National Instruments) and a personal computer (PC). The LCR meter and the current source are interconnected to the PC via a GPIB-USB interface. In turn, the DAQ is connected to the PC via a USB interface. The LCR meter is responsible for exciting the samples with the desired electrical current and performing measurements of the impedance phase. The Current source is used to excite the Helmholtz Coil in order to generate the external magnetic field to which the sample is subjected. On the other hand, the polarity inverter is used to invert the polarity of the current that flows through the Helmholtz Coil, inverting the direction of the generated magnetic field. The polarity is controlled by a digital output of the DAQ.

The system software runs on the PC and it is composed by two main modules: the control and measurement module, implemented in LabVIEW, and the optimization module, implemented in MatLab. The first module, is responsible for communicating with the equipment used in the system in order to control them and obtain the measurements of interest. The second module, is responsible for executing the optimization algorithm, based on genetic algorithms. The communication between these two modules is performed via TCP/IP protocol. Figure 1 shows a block diagram of the developed system.

![Diagram](image)

**Figure 1.** Basic setup of the system for automatic optimization of GMI samples sensitivity.
The control and measurement module receives the following parameters from the optimization module: $I_{DC}$, $f$ and $H_{pol}$. These parameters are the genes of each individual present in the GA population. In this way, the control and measurement module can properly configure the system equipment. In turn, the control and measurement module sends to the optimization module the phase readings of the sensor sample impedance, carried out under the conditions established by the optimization module. Two phase values are obtained for each individual, in order to estimate its phase sensitivity ($S_{phase}$). The phase measurements are performed at $H_{pol} - \Delta H$ and $H_{pol} + \Delta H$.

The phase sensitivity $S_{phase}$ is given by the derivative of the impedance phase ($\theta$) in relation to the applied external magnetic field ($H$). In turn, considering the characteristics of the problem addressed, $S_{phase}$ is defined as the fitness function of the genetic algorithm, and the higher the value of $S_{phase}$, the better the evaluated individual. As the analytical expressions of $\theta$ as a function of $H$ are not known, the derivative was approximated by the technique of numerical differentiation based on central differences, as described by equation (1).

$$S_{phase} = \frac{\theta(I_{DC}, f, H_{pol} + \Delta H) - \theta(I_{DC}, f, H_{pol} - \Delta H)}{2\Delta H}$$ (1)

All results presented in this work were calculated considering $\Delta H$ equal to 0.01 Oe.

The limits of each variable of the search space were established taken into account the working range of the equipment used in the optimization system. The bounds of the variables were settled to: $75 \text{ kHz} \leq f \leq 30 \text{ MHz}$, $0 \text{ mA} \leq I_{DC} \leq 100 \text{ mA}$ and $-2 \text{ Oe} \leq H_{pol} \leq 2 \text{ Oe}$.

The amplitude ($I_{dc}$) of the AC current was kept in $15 \text{ mA}$, because it has been previously seen that such parameter did not significantly affect the sensitivity of the GMI samples. The genetic algorithm was implemented in MatLab, using a population size of 100 individuals, maximum number of generations of 100, elitism criterion of 10 and the genetic operators chosen were heuristic crossover, adaptive mutation and tournament selection.

2.1. Dynamics of Operation
As shown in figure 2, the genetic algorithm is configured according to parameters defined by the user. Then, the genetic algorithm generates a random set of individuals that compose the initial population. These individuals are sent sequentially to the measurement and control system, which measures two phase values ($\theta$) to each of them, one at $H_{pol} - \Delta H$ and other at $H_{pol} + \Delta H$. The results of the measurements are sent back to the GA, that evaluates the aptitude of each individual by calculating their respective evaluation function – equation (1). At the end of this process, if a predefined stopping criterion is not reached, the individuals of the population are subjected to genetic operators in order to generate a new population, which will be evaluated by the same process here in described. The process is repeated until the genetic algorithm reaches the established stopping criterion. At the end of the GA evolution, the combination of parameters ($I_{DC}$, $f$ and $H_{pol}$) responsible for the maximum phase sensitivity is considered the best solution for the optimization problem.

Once the solution has been found, a characterization process is executed in order to evaluate the behaviour of the impedance phase of the analysed GMI sample in function of the magnetic field, for the optimal values of $I_{DC}$, $f$ and $H_{pol}$ returned by the genetic algorithm.
Figure 2. Flow diagram of the developed system.

3. Results and Analysis
The experimental measurements were carried out in a ribbon shaped Co$_{70}$Fe$_{2}$Si$_{18}$B$_{10}$ sample with 3 cm length, an average width of 1.5 mm and a thickness of 60 µm. This same sample was characterized in previous works [6], by other methodologies. In this way, the results obtained in the present work can be compared to the ones achieved in previous studies, presented in literature.

The developed genetic algorithm found a maximum sensitivity of 23.09°/Oe and took 31 generations to converge, spending an approximated time of 3.8 hours. The set of parameters of the individual that led to the maximization of the sensitivity is shown in table 1.

| Ind | $f$ (MHz) | $I_{DC}$ (mA) | $I_{AC}$ (mA) | $H_{pol}$ (Oe) | $S_{phase}$ (°/Oe) |
|-----|-----------|---------------|---------------|----------------|-------------------|
| Ind1 | 16.71     | 31.07         | 15            | -1.31          | 23.09             |
| Ind2 |
| Ind3 |
| Ind4 |
| Ind5 |
| Ind6 |
| Ind7 |
| Ind8 |
| Ind n |

Table 1. Results returned by the GA.

Figure 3 shows the characterization curve of the analysed GMI sample, excited by a current with DC level of 31.07 mA, amplitude of 15 mA and frequency of 16.71 MHz.

Figure 3. Impedance phase of the GMI sample in function of the external magnetic field, for an excitation current with 31.07 mA DC level, 15 mA amplitude and 16.71 MHz frequency.

In turn, the phase sensitivity $S_{phase}$ can be obtained by the derivative of the impedance phase with respect to the magnetic field. In this way, a numerical differentiation was applied to the phase curve presented in figure 3, aiming at obtaining their respective point-to-point sensitivity values, shown in figure 4. The results presented in figure 4 shows that the highest sensitivity achieved was 23.13 °/Oe at
$H = -1.31$ Oe. As expected, these values have good agreement with the values returned by the GA, which predicted a maximum sensitivity of $23.09^\circ$/Oe at $H = -1.31$ Oe.

Figure 4. Phase sensitivity in function of the external magnetic field, for the GMI sample subjected to a current with 31.07 mA DC level, 15 mA amplitude and 16.71 MHz frequency.

In order to evaluate the repeatability of the system, the same optimization process that led to the results indicated in table 1 was repeated two more times. The results obtained in each of the three performed tests are presented in table 3. Additionally, to the $S_{\text{phase}}$ and $H_{\text{pol}}$ values returned by the GA, table 3 also presents the maximum phase sensitivities obtained by the characterizations carried out after each optimization process ($S_{\text{characterization}}$), as well as the values of magnetic fields ($H_{\text{characterization}}$) corresponding to each $S_{\text{characterization}}$ obtained. The number of generations until the convergence of GA and the total computational processing time are presented for all tests performed.

Table 2. Analysis of the repeatability of the results obtained by the developed system.

|                      | Test 1 | Test 2 | Test 3 | Units   |
|----------------------|--------|--------|--------|---------|
| $S_{\text{phase}}$   | 23.09  | 22.96  | 22.87  | $^\circ$/Oe |
| $S_{\text{characterization}}$ | 23.13  | 23.57  | 23.83  | $^\circ$/Oe |
| $f$                  | 16.71  | 16.78  | 16.76  | MHz     |
| $I_{\text{DC}}$     | 31.07  | 34.58  | 40.49  | mA      |
| $I_{\text{AC}}$     | 15     | 15     | 15     | mA      |
| $H_{\text{pol}}$    | -1.31  | -1.33  | -1.34  | Oe      |
| $H_{\text{characterization}}$ | -1.31  | -1.32  | -1.34  | Oe      |
| Number of generations to convergence | 31     | 20     | 21     | generations |
| Processing time      | 3.8    | 2.4    | 2.7    | hours    |

According to the obtained results, the sensitivity values returned by the GA ($S_{\text{phase}}$) were always about $23^\circ$/Oe. Besides, the sensitivity values obtained by the characterization curves ($S_{\text{characterization}}$) were satisfactorily close to their respective $S_{\text{phase}}$ values. These results indicate a good repeatability of the developed algorithm.

In all of the tests performed, the frequency ($f$) was around 16.7 MHz; the biasing magnetic field ($H_{\text{pol}}$) was always close to -1.30 Oe and the amplitude of the alternating current ($I_{\text{AC}}$) was exactly the same, 15 mA, because this parameter was kept fixed. One can also notice that, as expected, $H_{\text{characterization}}$ was always near enough to $H_{\text{pol}}$. On the other hand, the DC current level have varied between 30 mA and 40 mA, which indicates that multiple values of $I_{\text{DC}}$ can lead to maximum phase sensitivities. Furthermore, table 2 indicates that the algorithm takes about 3 hours to converge to a solution.

Figure 5 shows the impedance phase characterization curves as a function of the magnetic field, for each of the three tests performed. Each characterization curve was obtained by adjusting to the excitation current ($i_c$) of the GMI sample according to the values of $I_{\text{DC}}$, $I_{\text{AC}}$ and $f$ specified in table 2.
Figure 5. Experimental characterization curves of the impedance phase as a function of external magnetic field, adjusting the excitation current of the GMI sample according to the values of \( I_{DC} \), \( I_{AC} \) and \( f \) specified in Table 2, for each test.

4. Conclusions
The developed optimization system is based on the concept of evolutionary hardware. It allows to adjust the operational point of GMI sensors, inserted in magnetometer circuits, aiming at improving their sensitivity. The system is controlled by a computational model based on genetic algorithms, implemented so that the genes of the individuals of the population represent the parameters of interest (\( I_{DC}, f \) and \( H_{pol} \)) that affect the sensitivity of the sensors (\( S_{phase} \)). The evaluation of the aptitude of each individual is done by experimental measurements. The system evolves towards the best combination of variables of interest (\( I_{DC}, f \) and \( H_{pol} \)) responsible for the maximization of the phase sensitivity.

The maximum sensitivity obtained was 23.83 °/Oe, which is about 2.5 times higher than the maximum sensitivity obtained in previous works published in literature (9.48 °/Oe) [6]. The developed system shows a good repeatability of the results and takes about 3 hours to converge to a solution. The achieved results allow to conclude that the developed system have implemented an effective automatized tool to define the set of variables that optimizes the phase sensitivity of GMI samples.

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