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Neuro-genetic system for optimization of GMI samples sensitivity

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ABSTRACT

Magnetic sensors are largely used in several engineering areas. Among them, magnetic sensors based on the Giant Magnetoimpedance (GMI) effect are a new family of magnetic sensing devices that have a huge potential for applications involving measurements of ultra-weak magnetic fields.

The sensitivity of magnetometers is directly associated with the sensitivity of their sensing elements. The GMI effect is characterized by a large variation of the impedance (magnitude and phase) of a ferromagnetic sample, when subjected to a magnetic field. Recent studies have shown that phase-based GMI magnetometers have the potential to increase the sensitivity by about 100 times.

The sensitivity of GMI samples depends on several parameters, such as sample length, external magnetic field, DC level and frequency of the excitation current. However, this dependency is yet to be sufficiently well-modeled in quantitative terms. So, the search for the set of parameters that optimizes the samples sensitivity is usually empirical and very time consuming.

This paper deals with this problem by proposing a new neuro-genetic system aimed at maximizing the impedance phase sensitivity of GMI samples. A Multi-Layer Perceptron (MLP) Neural Network is used to model the impedance phase and a Genetic Algorithm uses the information provided by the neural network to determine which set of parameters maximizes the impedance phase sensitivity.

The results obtained with a data set composed of four different GMI sample lengths demonstrate that the neuro-genetic system is able to correctly and automatically determine the set of conditioning parameters responsible for maximizing their phase sensitivities.

1. Introduction

Ribbons and wires made of soft ferromagnetic alloys have gained considerable attention due to their physical properties and technological applications. One of the most interesting phenomena observed is the Giant Magnetoimpedance (GMI). It began to be intensely investigated in the 1990s, taking the magnetoresistance examination in multilayer films as its starting point, in which it was observed a decrease in the electrical resistance when it was subjected to an external magnetic field (Machado, Martins, & Rezende, 1995; Machado, Silva, & Montarroyos, 1993; Machado, Silva, Rezende, & Martins, 1994).

Experimental results were published in 1993, suggesting the variation of the resistance with external magnetic fields in amorphous ribbons of composition $Co_{70.4}Fe_{4.6}Si_{15}B_{10}$ (50 μm thick, 1.5 mm wide and 1.5 cm long) (Machado et al., 1993) and in amorphous wires of $Co_{68.1}Fe_{4.4}Si_{12.5}B_{15}$ (120 μm diameter and 10 cm long) (Mandal and Ghatak, 1993). In both studies, the results obtained were interpreted as a variation of the Giant Magnetoresistance (GMR) effect, that is, the variation in the resistance of the samples as a function of the change in the movement of electrons when their spins are affected by the orientation of the magnetization in the material.

In the following year, the GMI effect was theoretically explained in the study by Beach and Berkowitz (1994), who not only coined the phenomenon by the current name, but were also the first ones to explain the effect based on the classical electrodynamics theory (Maxwell's equations), showing that the variation in impedance, as a result of the application of an external magnetic field, is, in fact, due to the variation in the penetration depth of electromagnetic waves, which depends on the angular frequency of the wave (ω), the magnetic permeability of the material (μ) and its electrical conductivity (σ).

Thus, the giant magnetoimpedance effect in amorphous magnetic materials is attributed to the fact that the impedance is inversely proportional to the current penetration depth, due to

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the skin effect. In turn, the latter depends on the frequency of the current applied, the geometry, and the magnetic permeability of the material, which may vary depending on the external magnetic field and the amplitude of the current that flows through the sample. This means that, in samples of a high permeability material, a variation in impedance as a function of the magnetic field can be expected even in an intermediate frequency band. Therefore, the GMI phenomenon basically reflects the dependence of the magnetic permeability with the magnetic field being applied (Phan & Peng, 2008).

The GMI effect is, then, characterized by the large variation of the impedance (magnitude and phase) of a ferromagnetic material sample, when subjected to an external magnetic field. The main advantages of magnetometers based on the GMI effect include their low cost for large-scale production, excellent sensitivity, portability and wide range of operating frequencies (Lenz & Edelstein, 2006; Mahdi, Panina, & Mapps, 2003; Phan & Peng, 2008).

The maximization of the sensitivity of magnetic transducers is directly associated with the optimization of the sensitivity of their sensing elements. In the case of using GMI samples, the development of a high-sensitivity magnetic transducer involves the maximization of the impedance phase and/or magnitude sensitivities of the sensing elements in relation to the external magnetic field.

In turn, such sensitivities are affected by several parameters such as amplitude, DC level and frequency of the excitation current, dimensions (length, width, thickness) and chemical composition of the sample material, biasing magnetic field (generated by an external source, in order to ensure that the sensor operates in its most sensitive range), temperature, among others (Costa Silva, Gusmão, Hall Barbosa, Costa Monteiro, & Machado, 2011; Hauser, Kraus, & Ripka, 2001; Kraus, 2003; Lenz & Edelstein, 2006; Mahdi et al., 2003; Phan & Peng, 2008; Pirota, Knobel, & Gomez-Polo, 2002). Therefore, the behavior of the impedance of GMI samples must be experimentally analyzed, aiming at finding the set of parameters that maximizes the sensitivity. However, due to the large number of variables, an exhaustive search along the entire sample space is unfeasible.

Also, recent studies have proven that magnetic transducers based on the impedance phase characteristics of the GMI effect have the potential to increase the sensitivity values by about 100 times (Costa Silva, Gusmão, Hall Barbosa, & Costa Monteiro, 2008, 2009, 2013; Costa Silva, Gusmão, & Costa Monteiro, 2014a; Costa Silva et al., 2011), as compared to magnitude-based transducers (Cavalcanti et al., 2008, 2006; Geliang, Xiongzhu, Bo, Yunlong, & Chao, 2011; Hauser et al., 2001; Lenz & Edelstein, 2006; Mahdi et al., 2003; Phan & Peng, 2008; Ramos Louzada, Costa Monteiro, Gusmão, & Hall Barbosa, 2007; Zhao, Yu, & Xiang, 2012). According to Costa Silva et al. (2014a, 2011), the sensitivity level reached by reading the phase characteristics allows the application of GMI magnetometers in the measurement of ultra-weak magnetic fields, down to the picotesla resolution.

From the experimental characterization of ribbon-shaped GMI samples with composition $Co_{70}Fe_5Si_{15}B_{10}$, Costa Silva et al. (2011) determined the set of conditioning parameters that most affects the impedance of the samples analyzed, which are the length of the sample, DC level and frequency of the excitation current, in addition to the external magnetic field.

Nowadays, the quantitative models proposed for the GMI effect are still not capable of properly dealing with all the parameters that affect the impedance of the samples, in a comprehensive and integrated manner (Hauser et al., 2001; Kraus, 2003; Phan & Peng, 2008; Pirota et al., 2002). This deficiency renders impossible the use of a conventional analytical optimization method, since the model does not depict the phenomenon itself in a sufficiently reliable manner. Therefore, the search for the set of parameters that optimizes the samples sensitivity is usually empirical.

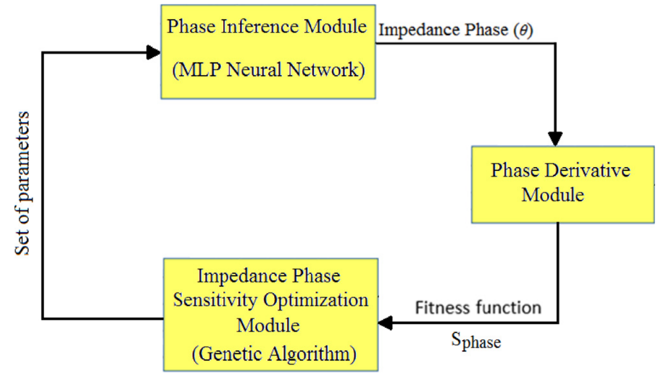

Fig. 1. Block diagram of the proposed Neuro-Genetic system.

On the other hand, computational intelligence techniques, such as artificial neural networks (ANN) and genetic algorithms (GA), have been successfully used in several application areas, sorting out problems that were difficult to be solved by conventional methods or problems with no alternative solution (Almeida, Hamacher, Pacheco, & Vellasco, 2003; Goldberg & Holland, 1988; Haykin, 1999; Holland, 2012; Varetto, 1998). In particular, recent works presented in the literature have applied ANN to the modeling of GMI behavior (Caylak & Derebasi, 2008; Derebasi, 2013; Kaya, 2013). However, these works do not address the optimization problem nor the analysis of the set of parameters that maximizes the sensitivity.

The present work addresses this specific issue by proposing a new neuro-genetic system to optimize the phase sensitivity, S_{phase}, of GMI samples. The developed model helps to determine the set of conditioning parameters (sample length, DC level and frequency of the excitation current, external magnetic field) that leads to the optimal phase sensitivity, S_{phase}, making the optimization process faster and more comprehensive. To the best of the authors' knowledge, there is no other computational system applied to the sensitivity optimization of GMI samples in the literature to date.

This paper is organized in three additional sections. Section 2 presents the proposed Neuro-Genetic Systems, detailing the three modules that are developed to optimize the phase sensitivity: the Phase Inference Module; the Phase Derivative Module; and the Impedance Phase Sensitivity Optimization Module. Section 3 describes the experiments carried out and the results obtained by each module. Section 4 provides some general conclusions of this work.

2. Neuro-Genetic system

As shown in Fig. 1, the proposed neuro-genetic system comprises three basic modules: (1) Phase Inference, (2) Phase Derivative, and (3) Impedance Phase Sensitivity Optimization.

The first module uses Artificial Neural Networks (ANNs) for modeling the impedance phase (θ) behavior of the samples as a function of the set of parameters that affect it. The output (θ) of the ANN is then connected to the Phase Derivative module that performs the differentiation of θ in relation to the external magnetic field (H), which is one of the input variables of the ANN. Therefore, the output of this second module is the phase sensitivity (S_{phase}), as defined in

$$S_{phase} = \frac{d\theta(H)}{dH}, \tag{1}$$

where θ is the impedance phase of the GMI sample and H is the external magnetic field.