A contactless ammeter based on GMR magnetometers

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Abstract. This work presents a contactless ammeter prototype based on GMR magnetometers, able to measure direct and alternating electrical currents. Two techniques were used to solve the inverse problem, which is, given the output voltages of the GMR sensors, to estimate the electric current flowing through the conductor - nonlinear curve fitting and artificial neural networks. The performance of both techniques was compared based on the standard uncertainty of the data calculated by each one. The results obtained with the neural networks are significantly better.

1. Introduction

Ammeters, essential for various applications in the industry, are instruments whose purpose is the measurement of electric currents in conductors. They can be of several types depending on the physical principle used for their implementation and on the need to interrupt the circuit for the current to be measured [1] [2] [3]. It is expected that the developed ammeter prototype will perform measurements of direct and alternating currents with high resolution, in relation to the present clamp ammeters based on coils and Hall effect sensors. The proposed system, initially presented in [2] [3], was developed with the purpose of also estimating the distance between the sensor and the conductor.

The main purpose in this work is to compare the performance of the technique used to solve the inverse problem, that is needed to estimate the current, previously presented in [3], nonlinear curve fitting, with artificial neural networks (ANN).

This paper is divided into: Section 2 presents the operating principle of giant magnetoresistance (GMR) magnetometers and how to use them to build an ammeter. Section 3 shows step by step how the data were acquired, pre-processed and selected. The computational results are described in Section 4. At last, Section 5 presents the conclusions.

2. Concepts

The following sections explain the operating principle of GMR magnetometers and how they are applied to the measurement of electric currents.

2.1. Giant magnetoresistance (GMR)

The basic operating principle of GMR is the variation of the resistance of a material as a function of an external magnetic field [4]. This variation, typically between 10 and 20 %, if compared to the maximum sensitivity of other magnetic sensors, is very large, hence the name giant magnetoresistance. Magnetoresistance can be found in classical semiconductors, particularly in magnetic semiconductors and, like the Hall effect, has its origin in the Lorentz force [4].
Although a single resistance can be used as a sensor element, the Wheatstone bridge configuration is a good recommendation because, in this topology, it is possible to obtain a differential voltage output as a function of the resistance variation [4] with lower influence of external factors such as temperature. In the development of this project it was used a commercial GMR, an integrated circuit, model AA005-02, manufactured by NVE Corporation [5]. The topology of the transducer is a Wheatstone half-bridge, having two magnetically shielded GMRs and two GMRs that are sensitive to the magnetic field. Without the presence of an external magnetic field the bridge is balanced and the output of the bridge is zero. In the presence of an external magnetic field, the field-sensitive GMRs change their values, unbalancing the bridge and generating a differential voltage output. The output signal of the bridge is directly proportional to the supply voltage/current, with a typical sensitivity of 0.45 mV/V/Oe.

2.2. GRM based ammeter

An electric current passing through a wire generates a circular magnetic field around it that varies with the intensity of the current and with the distance from the conductor to the measuring point [1]. By applying the Biot-Savart law to a straight conductor it is observed that the magnetic field $H$, measured at a distance $r_1$ from the conductor, is given by

$$H = \frac{I}{500r_1},$$

where $I$ is the electric current in amperes, $r_1$ is the distance between the conductor and the sensor in meters and $H$ is the magnetic field in oersteds (1 Oe = 1000/4$\pi$ A/m).

Analyzing Eq. (1), it is noticed that the use of only one GMR sensor is not sufficient, since it is necessary to know the distance $r_1$ to estimate the electric current $I$. Thus, a configuration has been previously proposed with two GMR sensors [2] [3], separated by a fixed distance ($D = 3$ cm), in addition to a permanent magnet that generates the magnetic field of 15 Oe (so that the sensor operates in its linear range), as shown in Figure 1.

By measuring the voltage generated by both GMR sensors it is possible to estimate the current $I$, regardless of the distance $r_1$ of the conductor from the sensors, and also estimate the distance $r_1$ between the sensor GMR1 and the conductor.

The electronic conditioning and reading circuit shown in Figure 2 was designed and implemented. The electronic circuit has the functions of feeding the GMR sensors with a DC current of approximately 3 mA (current source based on the LM318 operational amplifier), as well as reading the differential output voltage of the bridge and amplifying it by 50 times (instrumentation amplifier INA129, with gain defined by the 1 k$\Omega$ resistor). The offset voltage level of -5.0625 V allows a zero output voltage, $V_{out}$, to be obtained when $H = 15$ Oe (polarization field). Thus, for a current of 0 A in the wire, there will be an output of 0 V.
3. Acquisition, pre-processing and selection of data
To observe the effect of the hysteresis and any other fluctuations, ten tests with currents varying between -3 A and 3 A were performed, in steps of approximately 0.2 A. The result of the ten test cycles can be seen in Figure 3, containing 602 electrical current values and the respective output voltages.

To minimize sensor errors and improve the reliability of the measurements, the data were acquired using an A/D converter, model NI-USB 6001, with 14 bits resolution. In eight tests, for each sensor, an acquisition frequency of 10 kHz was used, with measurements taken every 2 s and, in two tests, with a frequency of acquisition of 6 kHz, and measurements taken every 3 s.

Analyzing Figure 3, it is possible to observe a variation on the signal offset, probably caused by the temperature effect or other external interferences. To solve this problem, and to remove the signal offset, the linear coefficient of the estimated trend lines for each test was excluded. Figure 4 shows the final data set and the overall trend lines, which show small linear coefficients and large determination coefficients ($R^2$).

Figure 2. Schematic diagram of the electronic conditioning circuit of GMR magnetometers.

Figure 3. Results of the ten test cycles measured by the 2 GMR sensors. Each color corresponds to one test cycle.

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4. Inverse Problem

As the objective is the development of an ammeter, it is necessary to solve the inverse problem, which is, given the output voltages of the GMR sensors, measured by the data acquisition system, to estimate the electric current flowing through the conductors. For that, two techniques were used: nonlinear curve fitting and artificial neural networks. The following subsections present the details of each of the techniques.

4.1. Artificial Neural Networks

A two-layer feed-forward network, with sigmoidal transfer function in the hidden layer and linear transfer function in the output layer was created using Matlab’s Neural Network Fitting Tool.

The final data set described in section 3 was randomly divided into training, validation and testing, respectively 70 %, 20 % and 10 % of the data. The network was trained with Levenberg-Marquardt backpropagation algorithm. Training process automatically stops when generalization stops improving, as indicated by an increase in the mean squared error (MSE) of the validation samples. The training process continued until the validation error failed to decrease for six iterations [6].

In order to determine the optimal number of neurons in the hidden layer, 5000 networks were trained, with the number of hidden neurons varying from one to fifty. For each number of neurons, a hundred networks were trained and it was calculated an average Root Mean Squared Error (RMSE) for training and validation data. After repeating these tests five times, it has been obtained an average RMSE around 68-78 mA and a maximum improvement with the number of neurons around 8 mA.

Considering the results obtained previously, a small number of neurons in the hidden layer already presents satisfactory results to solve the proposed problem. Thus, the tests were performed using 5 and 10 neurons in the hidden layer. For each number of neurons, the neural networks were trained 50 times, and the one with best validation RMSE was chosen for testing. The following steps show the performance results for both networks.

The regression analysis in Figure 5 and Figure 6 shows that the data estimated by the neural networks are strongly correlated with the experimental data, with values of R (correlation coefficient) higher than 0.999 for validation, training and testing steps, for both network configurations.
At last, the test RMSE was calculated (Table 1) for each network. The network can predict the electrical current value, given the GMRs voltage values, with high accuracy, with errors around 71 – 76 mA.

Table 1. Test RMSE vs Hidden layer neurons

| Hidden layer neurons | RMSE values [mA] |
|----------------------|------------------|
| 5                    | 71.76            |
| 10                   | 76.72            |

4.2. Nonlinear curve fitting

To solve the nonlinear curve fitting problem, described in Eqs. (2) to (5), it was used Matlab’s function “lsqcurvefit”, which adjusts the parameters of the problem, minimizing the error between the theoretical and experimental data. Given the arrangement of the system, the output voltages of the circuit can be deduced from the electric current and several parameters. For a specific sensor \( n \), Eqs. (2) to (5) present a step-by-step calculation of the output voltage in the circuit \( V_n \) as a function of current \( I \), sensor sensitivity \( K_n \), the magnetic field related to the permanent magnet \( H_{0n} \), the offset voltage in the sensor due to internal factors \( V_{0n} \), the INA129 gain \( G_n \) and the offset voltage \( V_{offn} \) of the INA129. \( H_n \) represents the magnetic field at which the sensor is located and \( V_n \) represents the output voltage of the circuit, which is measured by the data acquisition system.

\[
H_n = \frac{I}{2\pi r} + H_{0n} \quad (2)
\]

\[
V_{NGMR} = K_n H_n + V_{0n} \quad (3)
\]

\[
V_n = V_{NGMR} G_n + V_{offn} \quad (4)
\]

\[
V_n = K_n \left( \frac{I}{2\pi r} + H_{0n} \right) + V_{0n} G_n + V_{offn} \quad (5)
\]

By means of the data and the analytical equation, the “lsqcurvefit” function of Matlab, the values of the parameters that best fit the problem are estimated, in order to generate a function that follows the phenomenon and is better approximated to the experimental data, in terms of the mean squared error.
For this, it is necessary to choose initial values for the parameters to be optimized, as well as limits (upper and lower) for the parameters, as indicated in Table 2.

**Table 2. Parameters for the nonlinear curve fitting algorithm.**

| Parameter | Initial value | Lower Limit | Upper Limit |
|-----------|---------------|-------------|-------------|
| $K_1$ and $K_2$ | 6.75 mV/Oe | 6.75 mV/Oe | 9.75 mV/Oe |
| $r_1$ | 0.01 m | 0.008 m | 0.012 m |
| $r_2$ | 0.04 m | 0.038 m | 0.042 m |
| $H_{01}$ and $H_{02}$ | 15 Oe | 13.5 Oe | 16.5 Oe |
| $V_{01}$ and $V_{02}$ | 0 V | -100 mV | 100 mV |
| $G_1$ and $G_2$ | 50 | 49 | 51 |
| $V_{off1}$ and $V_{off2}$ | -5.0625 V | -6 V | $+\infty$ V |

The data were processed and the optimal parameters found, as indicated in Table 3, and used to calculate Eqs. (6) and (7) of the output voltage in the circuits as a function of the current in the conductor and the distance $r_1$ to the sensor 1.

**Table 3. Optimal parameters found by the curve fitting algorithm.**

| Parameter | Optimal value | Parameter | Optimal value |
|-----------|---------------|-----------|---------------|
| $K_1$ | 6.7500 mV/Oe | $V_{03}$ | 6.5 mV |
| $K_2$ | 6.7500 mV/Oe | $V_{02}$ | 35.6 mV |
| $r_1$ | 1.1929 cm | $G_1$ | 49.0273 |
| $r_2$ | 4.200 cm | $G_2$ | 49.0000 |
| $H_{01}$ | 15.0470 Oe | $V_{off1}$ | -4.9799 V |
| $H_{02}$ | 14.5058 Oe | $V_{off2}$ | -4.7995 V |

Finally, in order to verify the reliability of the system, the respective current values were calculated for the different output voltage values of the GMRs obtained in section 3. Figure 7 shows the graph of the measured points, where the x-axis represents the nominal current values and the y-axis represents the current values calculated by means of Eqs. (6) and (7).

\[
V_1 = \frac{I}{r_1 + 0.0029}
\]  
\[
V_2 = \frac{I}{r_1 + 0.03} + 0.0087
\]  

![Figure 7. Nominal vs calculated current values.](image)
5. Discussion and conclusions

The performance of both techniques was compared based on the standard uncertainty of data calculated by each one, as given by Table 4.

| Method                  | Uncertainty [A] |
|-------------------------|-----------------|
| Nonlinear regression    | 0.54006         |
| ANN with 5 neurons      | 0.07133         |
| ANN with 10 neurons     | 0.07052         |

The results show that the artificial neural networks technique fits much better the solution of this problem. In future works we intend to study the effects of temperature and to magnetically isolate the sensor, as well as improvements in the conditioning circuit, in order to eliminate the offset variations and interferences observed and obtain more consistent data, so as to improve the obtained uncertainty.

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