





# Article Magnetic Noise Prediction and Evaluation in Tunneling Magnetoresistance Sensors

## Jakub Chęciński <sup>1,2,\*</sup>, Piotr Wiśniowski <sup>1</sup>, Marek Frankowski <sup>1</sup> and Tomasz Stobiecki <sup>1,2</sup>

- <sup>1</sup> Department of Electronics, AGH University of Science and Technology, Al. Mickiewicza 30, 30-059 Kraków, Poland; piotr.wisniowski@agh.edu.pl (P.W.); mfrankow@agh.edu.pl (M.F.); stobieck@agh.edu.pl (T.S.)
- <sup>2</sup> Faculty of Physics and Applied Computer Science, AGH University of Science and Technology, Al. Mickiewicza 30, 30-059 Kraków, Poland
- \* Correspondence: jchecin@agh.edu.pl

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**Abstract:** We propose a simple model for prediction of magnetic noise level in tunneling magnetoresistance (TMR) sensors. The model reproduces experimental magnetic 1/f and white noise components, which are dependent on sensors resistance and field sensitivity. The exact character of this dependence is determined by comparing the results with experimental data using a statistical cross-validation procedure. We show that the model is able to correctly predict magnetic noise level for systems within wide range of resistance, volume and sensitivity, and that it can be used as a robust method for noise evaluation in TMR sensors based on a small number of easily measurable parameters only.

**Keywords:** magnetic field sensing; tunneling magnetoresistance devices; noise modeling; 1/f noise; white noise

## 1. Introduction

Magnetic field detection by high sensitivity sensors based on tunneling magnetoresistive (TMR) devices has great potential for applications where high sensitivity, wide dynamic range, high spatial resolution and low power consumption are important. These sensors can be used in low and ultra-low magnetic field detection (biosensing and compass), high performance rotation and angle measurements (motor shaft, steering wheel, and anti-lock braking system) and current sensing (over current protection and high speed current monitoring) [1–4]. In most of these applications, the field detection, which is determined by the field sensitivity and noise level of the sensors, is the critical parameter that determines a sensor performance.

In principle, the sensors present both electronic and magnetic noise. It has been shown (see, e.g., [5,6]), however, that the magnetic noise dominates the electronic noise in high sensitivity TMR sensors. The magnetic noise appears during the sensing layer magnetization rotation between the saturated states of a resistance vs. magnetic field (*R*-*H*) curve (i.e., a transfer curve) and contains frequency dependent (1/f) and frequency independent (white) components. Both noise components depend on bias conditions as well as on several specific TMR sensors materials and design parameters [7–9], such as sensing layer volume, saturation magnetization, anisotropy field, Gilbert damping and susceptibility.

However, for predicting TMR sensors magnetic field detection performance, it is of great importance to have a few easily measurable sensor parameters that could be used to estimate the noise level of the sensors. Indeed, it has been shown that the magnetic noise of TMR sensors strongly correlates with derivative of a transfer curve (dR/dH) [5,10,11]. Therefore, we can define field sensitivity (*FS*) as a product of sensors bias current ( $I_b$ ) and the derivative,  $FS = I_b dR/dH$ . Because dR/dH depends

on the resistance of the sensor, both the resistance and field sensitivity can be used to predict and evaluate the sensor's noise and therefore the field detection.

To predict magnetic noise level of the TMR sensors, we developed a simple model that generates 1/f and white noise components. These components are related to sensor resistance and field sensitivity by polynomial dependencies. We show that the model sufficiently accurately reproduces experimental noise. Thus, it can be used for effective and robust prediction and evaluation of magnetic noise in TMR sensors with very different (three orders of magnitude range) values of resistance and field sensitivity.

#### 2. Methods

To reproduce magnetic noise of TMR sensors, we introduce fluctuation of magnetization angle  $\theta$  of the sensing layer with respect to the reference layer. The angle fluctuates in time, and the fluctuation behavior is controlled by two independent stochastic processes, one that produces frequency dependent noise (1/f-like) and another that produces frequency independent noise (white noise) (see Figure 1). The amplitudes of these two processes,  $A_{1/f}$  and  $A_{white}$ , respectively, are the numerical parameters of the model, which will control the noise generation. To provide a quantitative prediction of noise levels, these parameters are tied to easily measurable sensor parameters such as resistance and field sensitivity, as described in Section 3.



**Figure 1.** Illustration of the magnetic noise model. Both 1/f noise and white noise contribute to the small angle fluctuations of the sensing layer magnetization.

By describing the sensing layer of a TMR sensor with a single angle quantity, we can obtain a time series that corresponds to fluctuating magnetization. We used a standard formula for tunnel magnetoresistance of TMR sensors:

$$R(\theta) = \frac{R_{AP} + R_P}{2} - \frac{R_{AP} - R_P}{2} \cdot \cos\theta \equiv R_0 - \Delta R \cdot \cos\theta, \tag{1}$$

where resistance *R* depends on the angle  $\theta$  between the reference and the sensing layer magnetization and  $R_{AP}$  and  $R_P$  are resistances of anti-parallel and parallel state, respectively. Since we were interested in sensors operating in the highest sensitivity point on the transfer curve,  $\theta$  was close to 90° in our case, with the deviations from 90° originating from fluctuating magnetization generated by the stochastic processes:

$$\theta(t) = \theta_0 + \delta\theta(t) \approx 90^\circ + \delta\theta(t), \tag{2}$$

$$\delta\theta(t) = A_{1/f}\varepsilon_{1/f}(t) + A_{white}\varepsilon_{white}(t), \tag{3}$$

where  $\varepsilon_{1/f}$  and  $\varepsilon_{white}$  represent the stochastic processes generating normalized noise with unit variance of 1/f and white characteristics, respectively. Once the resistance time series was obtained, we multiplied the result by the bias current to obtain voltage as a function of time V(t). We performed Fast Fourier Transform on V(t) to receive a frequency-domain noise output. An example result, averaged 50 times, is shown in Figure 2a for 1/f-like stochastic process (black), white noise-like stochastic process (red) and both processes acting simultaneously (blue). For reference, the figure also includes example V(t) curves in the presence of 1/f-like (Figure 2b) and white noise-like (Figure 2c) stochastic process.



**Figure 2.** An example frequency-domain output (**a**) generated by 1/f-like stochastic process (**b**) and white noise-like stochastic process (**c**).

To produce a noise characteristic with our noise model, we need to provide sensors and stochastic process parameters and bias conditions. Thus, we need to know the values of  $R_0$  and  $\Delta R$  (or, equivalently,  $R_P$  and  $R_{AP}$ ) as defined in Equation (1), the bias current  $I_b$  (or, equivalently, bias voltage  $V_b$ ) and to specify the values of two amplitudes  $A_{1/f}$  and  $A_{white}$  connected with the stochastic processes. In the next section, we describe an algorithm to determine the relationship between  $A_{1/f}$  and  $A_{white}$  and the experimental quantities  $R_0$ ,  $\Delta R$ ,  $V_b$ , FS, and  $\Omega$  (where  $V_b$  is the bias voltage, equal to the product of  $R_0$  and  $I_b$ , and  $\Omega$  is the sensing layer volume). We show that these quantities, which are commonly used in sensor technology, can provide full information needed to predict the noise characteristics for a given sensor.

## 3. Results

#### 3.1. Sensors Noise

To determine the relationship between  $A_{1/f}$  and  $A_{white}$  and the sensor parameters such as resistance and field sensitivity, we measured noise for TMR sensors with wide resistance range (from 13  $\Omega$  to 6250  $\Omega$ ), volume of the free layer (0.029  $\mu$ m<sup>3</sup> to 13  $\mu$ m<sup>3</sup>) and field sensitivity (from 0.3 V/T to 225 V/T) (see Figure 3a). Further details about the sensors can be found in [12,13]. The sensors' noise (Figure 3b) was measured in a shielded doubled wall box, containing battery-powered low-noise amplifiers (voltage noise 4.7 nV/Hz<sup>0.5</sup> and 6.4 nV/Hz<sup>0.5</sup>), voltage bias circuit, and a pair of coils generating a bias magnetic field. The noise power spectral density was recorded by the spectrum analyzer technique.



**Figure 3.** Resistance and field sensitivity of TMR sensors (**a**). Noise characteristics of selected sensors with different resistance, volume and field sensitivity values (**b**).

For each measured sensor noise characteristic, we performed several thousand simulations based on our model with different pairs of  $A_{1/f}$  and  $A_{white}$  values to find the pair that would produce the best match with the measured noise. An example result can be seen in Figure 4, where we show three experimental characteristics superimposed onto their best fitting matches in the model. The final  $A_{1/f}$ and  $A_{white}$  parameters, determined for all investigated samples and normalized to 1 µm<sup>3</sup> sensing layer volume, are listed in Appendix A. The next step is to identify the dependence between the obtained  $A_{1/f}$ ,  $A_{white}$  and selected experimental parameters.



**Figure 4.** Comparison between experimental noise characteristics (solid black line) and their corresponding best matches in the model (transparent red line) obtained for three representative sensors.

#### 3.2. Noise Prediction and Evaluation

To predict the noise levels of TMR sensors using our model, we performed a statistical analysis scheme. The scheme was based on cross-validation technique, which is commonly utilized in statistics and data science [14,15]. Since we already accounted for the sensing layer volume  $\Omega$  by normalizing the noise coefficients, only four possible independent predictors— $R_0$ ,  $\Delta R$ ,  $V_b$  and FS—remained. However, we found that the correlation between  $R_0$  and  $\Delta R$  was very strong (correlation coefficient  $\rho_{R_0,\Delta R} > 0.98$ ), so that models containing both variables could be statistically unreliable. As a result, we decided to

drop  $\Delta R$  from the possible predictors list and use  $R_0$  only. We note here that  $R_0$  displayed stronger correlations with both target variables,  $A_{1/f}$  and  $A_{white}$ , than  $\Delta R$  (-0.67 and -0.82 vs. -0.59 and -0.77, respectively), making it a better candidate for a predictor.

The available data points ( $R_0$ , Vb, and FS) were randomly divided into N = 5 different sets of equal size. During each of N steps of the employed algorithm, a different one of those sets was treated as a validation sample, whereas all the others were treated as a training sample for a model candidate. Since the candidate model was fitted using only the training set part of the data, the comparison between its prediction and the actual noise level registered in the validation set part of the data provides a good estimate of the prediction error. By minimizing this prediction error, we can avoid overfitting and obtain a model that will be able to estimate noise levels of TMR sensors. Because of vast differences among sensor parameter levels (multiple orders of magnitude), we decided to perform the cross-validation scheme based on logarithmized quantities, as depicted in Table A1 in Appendix A.

We tested different regression models, using cross-validation error as the criterion for comparing them to each other. We considered the following set of possible predictor variables:  $\{R_0, FS, V_b, (R_0)^2, (FS)^2, (V_b)^2, (R_0)^3, (FS)^3, (V_b)^3, R_0 \cdot FS, R_0 \cdot V_b, FS \cdot V_b, (R_0)^2 \cdot FS, (R_0)^2 \cdot V_b, R_0 \cdot (FS)^2, R_0 \cdot (V_b)^2, (FS)^2 \cdot V_b, FS \cdot (V_b)^2\}$ . Each model was constructed by selecting a subset of variables from this set and fitting the resultant expression to the available data using the previously described approach. Because of the large amount of possible combinations, we utilized the forward stepwise regression scheme [14,15] for both  $A_{1/f}$  and  $A_{white}$ . As a result, we obtained the following formulas for noise amplitude prediction:

$$A_{1/f} = -0.20FS - 0.39R_0 - 0.59V_b + 0.35(FS)^2 - 1.98,$$
(4a)

$$A_{white} = -0.70FS + 1.13R_0 - 0.86V_b - 0.37R_0^2 + 0.26(FS)^2 + 0.22R_0 \cdot FS - 1.97,$$
 (4b)

where all variables are logarithmized using logarithm with base 10. An illustration of the formulas can be seen in Figure 5, where the prediction based on Equation (4a) and (4b) (red line) is plotted together with experimental data (black squares) for both 1/f-type noise (Figure 5a) and white noise (Figure 5b). The statistical coefficients of determination  $R^2$  were equal to approximately 0.86 for 1/f-type noise and 0.95 for white noise, which means that in both cases more than 85% of the experimental data variance can be explained using our model. The remaining part, which the model is unable to explain, can be attributed to measurement errors, insufficient precision or more complicated physical effects that cannot be captured by a simple regression approach.

The obtained noise levels can be used to determine quantities that are easily measurable in an experiment, for example the root mean square (RMS) voltage of noise  $V_{RMS}$ . To obtain the expression for RMS in our model, Equation (1) can be rewritten in the following way:

$$R(\theta) = R_0 - \Delta R \cdot \cos \theta = R_0 - \Delta R \cdot \cos \left( \theta_0 + A_{1/f} \varepsilon_{1/f} + A_{white} \varepsilon_{white} \right), \tag{5}$$

For small angle fluctuations and  $\theta_0$  close to 90° (which is typical for highest sensitivity point on the transfer curve), we obtain:

$$V(\varphi) \approx I_b \Big( R_0 + \Delta R \cdot \Big( A_{1/f} \varepsilon_{1/f} + A_{white} \varepsilon_{white} \Big) \Big), \tag{6}$$

$$V_{RMS} \approx I_b \Delta R \sqrt{\left(A_{1/f}\right)^2 + \left(A_{white}\right)^2}.$$
(7)



**Figure 5.** Illustration of the model prediction found for: 1/f-type noise (**a**); and white noise (**b**). In both charts, the respective noise coefficient is shown as a function of the specific expression identified, for both the regression model (red line) and the experimental data (black squares). All variables presented in this chart are logarithmized.

By combining the obtained results, we can propose a simple method to calculate approximate value of  $V_{RMS}$  in an TMR sensor based only on easily measurable quantities:

- (1). Gather information about  $R_0$  ( $\Omega$ ),  $\Delta R$  ( $\Omega$ ), FS (V/T) and  $I_b$  (mA) from the experimental data. Typically, the last two quantities will be available in an explicit form. The first two may be intertwined with other parameters and available either only as information about resistances of parallel and anti-parallel state ( $R_P$  and  $R_{AP}$ ) or as information about minimal and maximal voltage levels on the U(H) curve ( $U_{min}$  and  $U_{max}$ , respectively). In that case, one can recall that in our model  $R_0 = (R_{AP} + R_P)/2 = (U_{max} + U_{min})/(2 \cdot I_b)$  and  $\Delta R = (R_{AP} R_P)/2 = (U_{max} U_{min})/(2 \cdot I_b)$ .
- (2). Use Equation (4a) and (4b) to calculate  $A_{1/f}$  as well as  $A_{white}$  values. It is important to note that these equations are given in a form where all variables are logarithmized using logarithm with base 10.
- (3). Normalize the calculated  $A_{1/f}$  and  $A_{white}$  values, dividing them by the sensing layer volume  $\Omega$  expressed in  $\mu$ m<sup>3</sup> units.
- (4). Use the obtained  $A_{1/f}$  and  $A_{white}$  together with Equation (7) to calculate  $V_{RMS}$ .

By following this procedure, we gathered model predictions for  $V_{RMS}$  in all of our measured TMR sensor samples and compared them with the experimental data. The experimental  $V_{RMS}$  values of noise were computed from power spectral noise density using the formula:

$$V_{RMS,experimental} = \sqrt{\int_{f_L}^{f_H} S_v df},$$
(8)

where  $f_L$  and  $f_H$  are lowest and highest frequencies of measured noise, respectively, and  $S_v$  is the noise power spectral density. We also computed standard deviation of the noise measured in time domain for a few selected sensors, and obtained  $V_{RMS}$  values similar (difference below 10%) to the ones given by Equation (8). The comparison between experimental and model  $V_{RMS}$  values can be seen below in the Figure 6. One can see that a good agreement is reached for nearly all measured samples, despite their very wide range of resistance and sensitivity values, which has a span of almost three orders of magnitude in both cases.



**Figure 6.** Root mean square value of voltage noise compared for model prediction (red line) and experimental data (black squares). The scale of both axes is logarithmic.

Overall, we would like to emphasize that the sensor data used to calibrate our model showed a great variety not only in terms of resistance and sensitivity, but also shape, size and sensing layer composition (see Table A2 in Appendix A). Therefore, we believe that our findings can be applied for most TMR sensors based on CoFeB/MgO/CoFeB structure with planar sizes on the order of 2–100  $\mu$ m and typical sensing layer CoFeB compositions, regardless of their detailed shapes, composition ratios or sample preparation technologies.

## 4. Conclusions

We proposed a simple model for magnetic noise levels prediction in TMR sensors that is based on easily measurable quantities such as field sensitivity and resistance. Noise measurements for a wide variety of sensors, characterized by resistance values ranging from 13  $\Omega$  to 6250  $\Omega$  and field sensitivity values ranging from 0.3 V/T to 225 V/T, were performed. The experimental data were then used as the basis for a statistical approach based on polynomial regression together with cross-validation to identify the optimal formula for noise prediction. For both 1/f and white noise, we were able to explain over 85% of the experimental data variance using the obtained formula. We also calculated RMS value of noise and compared it with the values retrieved from the experimental data. The presented model can be used as a robust method for predicting approximate magnetic noise in TMR sensors based on basic experimental quantities.

**Author Contributions:** J.Ch., P.W. and M.F. designed the model; P.W. performed the sensor measurements; J.Ch. performed the statistical analysis; J.Ch., P.W., M.F. and T.S. participated in results analysis and manuscript preparation.

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Conflicts of Interest: The authors declare no conflict of interest.

## Appendix A

The overview of the gathered data can be seen in Table A1. Since the relevant experimental values differed from each other by multiple orders of magnitude, we decided to perform our analysis using logarithmized variables for resistance, sensitivity and current as well as for noise levels. Please note that the TMR ratios, which can be determined from the expression TMR =  $(R_{AP} - R_P)/R_P = 2\Delta R/(R_0 - \Delta R)$ , are influenced by high bias voltages (up to 1000 mV). This happened because we were interested in devices working close to maximum sensitivity bias point, which typically requires higher voltage and thus decreased TMR value.

No.	R <sub>0</sub> (Ω)	Δ <i>R</i> (Ω)	FS (V/T)	<i>Ib</i> (mA)	Ω (μm³)	A <sub>1/f</sub>	Awhite	log <sub>10</sub> (R <sub>0</sub> )	$log_{10}$ ( $\Delta R$ )	log <sub>10</sub> (FS)	$log_{10}$ ( $V_b$ )	$log_{10}$ ( $A_{1/f}$ )	$log_{10}$ ( $A_{white}$ )
1	6250	1250	1.9	0.008	0.029	$8.02  imes 10^{-4}$	$1.79 imes10^{-3}$	3.80	3.10	0.28	1.70	-3.10	-2.75
2	6200	1200	3.8	0.017	0.029	$6.17 imes10^{-4}$	$9.87 imes10^{-4}$	3.79	3.08	0.58	2.02	-3.21	-3.01
3	5650	1150	22	0.09	0.041	$1.36 imes10^{-3}$	$9.26 imes10^{-4}$	3.75	3.06	1.34	2.71	-2.87	-3.03
4	5600	800	11	0.054	0.029	$4.13 imes10^{-4}$	$5.06 imes10^{-4}$	3.75	2.90	1.04	2.48	-3.38	-3.30
5	3950	825	1.65	0.0125	0.042	$5.74 imes10^{-4}$	$8.64 imes10^{-4}$	3.60	2.92	0.22	1.69	-3.24	-3.06
6	3800	400	25	0.21	0.029	$4.50  imes 10^{-4}$	$6.05  imes 10^{-4}$	3.58	2.60	1.40	2.90	-3.35	-3.22
7	3700	650	7.6	0.08	0.042	$3.27  imes 10^{-4}$	$4.07  imes 10^{-4}$	3.57	2.81	0.88	2.47	-3.49	-3.39
8	3400	500	10.4	0.15	0.042	$3.33  imes 10^{-4}$	$8.64 imes10^{-4}$	3.53	2.70	1.02	2.71	-3.48	-3.06
9	1925	375	1.55	0.027	0.16	$4.01 \times 10^{-4}$	$1.30 \times 10^{-3}$	3.28	2.57	0.19	1.72	-3.40	-2.89
10	1925	375	1.52	0.027	0.16	$3.46 \times 10^{-4}$	$9.26  imes 10^{-4}$	3.28	2.57	0.18	1.72	-3.46	-3.03
11	1900	350	3.1	0.054	0.16	$3.46  imes 10^{-4}$	$9.26  imes 10^{-4}$	3.28	2.54	0.49	2.01	-3.46	-3.03
12	1900	350	2.83	0.055	0.16	$2.53 \times 10^{-4}$	$8.02 \times 10^{-4}$	3.28	2.54	0.45	2.02	-3.60	-3.10
13	1700	250	14.1	0.3	0.16	$2.78 \times 10^{-4}$	$6.79  imes 10^{-4}$	3.23	2.40	1.15	2.71	-3.56	-3.17
14	1700	250	9.2	0.32	0.16	$1.48  imes 10^{-4}$	$3.02 \times 10^{-4}$	3.23	2.40	0.96	2.74	-3.83	-3.52
15	1525	225	6	0.33	0.16	$2.78  imes 10^{-4}$	$2.47  imes 10^{-4}$	3.18	2.35	0.78	2.70	-3.56	-3.61
16	1150	125	23.6	0.89	0.16	$1.48 \times 10^{-4}$	$5.31 \times 10^{-4}$	3.06	2.10	1.37	3.01	-3.83	-3.28
17	1020	100	10.1	0.98	0.16	$8.64 \times 10^{-5}$	$1.79 \times 10^{-4}$	3.01	2.00	1.00	3.00	-4.06	-3.75
18	315	15	0.3	1.55	0.56	$6.97 \times 10^{-5}$	$5.18 \times 10^{-4}$	2.50	1.18	-0.52	2.69	-4.17	-3.29
19	110	25	127	4.5	0.92	$1.30 \times 10^{-3}$	$1.60 \times 10^{-3}$	2.04	1.40	2.10	2.69	-2.89	-2.79
20	107.5	22.5	110	4.8	0.92	$2.72 \times 10^{-4}$	$1.36 \times 10^{-3}$	2.03	1.35	2.04	2.71	-3.57	-2.87
21	105	20	58	4.6	0.92	$1.54 \times 10^{-4}$	$9.26 \times 10^{-4}$	2.02	1.30	1.76	2.68	-3.81	-3.03
22	102.5	22.5	120	5.2	0.92	$1.05 \times 10^{-3}$	$1.17 \times 10^{-3}$	2.01	1.35	2.08	2.73	-2.98	-2.93
23	100	15	12.7	5	0.92	$7.40 \times 10^{-5}$	$4.13  imes 10^{-4}$	2.00	1.18	1.10	2.70	-4.13	-3.38
24	100	15	6.5	5.1	0.92	$2.47 \times 10^{-5}$	$3.09 \times 10^{-4}$	2.00	1.18	0.81	2.71	-4.64	-3.51
25	100	15	2.7	4.9	0.92	$3.09 \times 10^{-5}$	$1.85 \times 10^{-4}$	2.00	1.18	0.43	2.69	-4.56	-3.73
26	90	25	23.3	0.55	3.61	$1.48 \times 10^{-4}$	$7.40 \times 10^{-4}$	1.95	1.40	1.37	1.69	-3.83	-3.13
27	72.5	12.5	158	6.6	3.61	$4.75 \times 10^{-4}$	$3.76 \times 10^{-4}$	1.86	1.10	2.20	2.68	-3.32	-3.42
28	50	9	6.8	9.9	2.50	$3.09 \times 10^{-5}$	$1.11 \times 10^{-4}$	1.70	0.95	0.83	2.69	-4.51	-3.95
29	48	10	23	10.2	2.50	$4.94 \times 10^{-5}$	$2.10 \times 10^{-4}$	1.68	1.00	1.36	2.69	-4.31	-3.68
30	48	8	3.9	10.4	2.50	$1.85 \times 10^{-5}$	$1.05 \times 10^{-4}$	1.68	0.90	0.59	2.70	-4.73	-3.98
31	46	7	2.3	10.2	2.50	$1.23 \times 10^{-5}$	$1.23 \times 10^{-4}$	1.66	0.85	0.36	2.67	-4.91	-3.91
32	17	3	1.54	30.5	9.90	$4.94 \times 10^{-5}$	$3.70 \times 10^{-5}$	1.23	0.48	0.19	2.71	-4.31	-4.43
33	15.5	1.5	0.32	32	9.31	$1.23 \times 10^{-5}$	$5.55 \times 10^{-5}$	1.19	0.18	-0.49	2.70	-4.91	-4.26
34	13	4	225	37	13.0	$1.36 \times 10^{-4}$	$1.85 \times 10^{-5}$	1.11	0.60	2.35	2.68	-3.87	-4.73

**Table A1.** Overview of measurement data and fitting results. Before logarithmizing, resistance values were given in Ohms, sensitivity values in V/T and current values in mA. The values of  $A_{1/f}$  and  $A_{white}$  were normalized to 1  $\mu$ m<sup>3</sup> volume of the sensing layer.

In addition to the measurement data, we present selected physical and technological characteristics of the sensors used for calibration in Table A2.

**Table A2.** Selected physical and technological characteristics of the TMR sensors used for calibration. In the sensing layer deposition method column, "standard" refers to DC standard magnetron sputtering and "linear dynamic" refers to linear dynamic DC magnetron sputtering deposition.

No.	Planar Shape	Planar Size (µm)	Sensing Layer Composition	Sensing Layer Deposition Method		
1	rectangle	$2.5 \times 7.5$	(Co <sub>52</sub> Fe <sub>48</sub> ) <sub>75</sub> B <sub>25</sub>	standard		
2	rectangle	2.5  imes 7.5	(Co <sub>52</sub> Fe <sub>48</sub> ) <sub>75</sub> B <sub>25</sub>	standard		
3	square	$5 \times 5$	Co <sub>20</sub> Fe <sub>60</sub> B <sub>20</sub>	linear dynamic		
4	rectangle	$2.5 \times 7.5$	(Co <sub>52</sub> Fe <sub>48</sub> ) <sub>75</sub> B <sub>25</sub>	standard		
5	rectangle	$3 \times 9$	$(Co_{52}Fe_{48})_{75}B_{25}$	standard		
6	rectangle	$2.5 \times 7.5$	(Co <sub>52</sub> Fe <sub>48</sub> ) <sub>75</sub> B <sub>25</sub>	standard		
7	rectangle	$3 \times 9$	$(Co_{52}Fe_{48})_{75}B_{25}$	standard		
8	rectangle	$3 \times 9$	$(Co_{52}Fe_{48})_{75}B_{25}$	standard		
9	rectangle	$2 \times 36$	(Co <sub>52</sub> Fe <sub>48</sub> ) <sub>75</sub> B <sub>25</sub>	standard		
10	rectangle	$2 \times 36$	(Co <sub>52</sub> Fe <sub>48</sub> ) <sub>75</sub> B <sub>25</sub>	standard		
11	rectangle	$2 \times 36$	(Co <sub>52</sub> Fe <sub>48</sub> ) <sub>75</sub> B <sub>25</sub>	standard		
12	rectangle	$2 \times 36$	(Co <sub>52</sub> Fe <sub>48</sub> ) <sub>75</sub> B <sub>25</sub>	standard		
13	rectangle	$2 \times 36$	(Co <sub>52</sub> Fe <sub>48</sub> ) <sub>75</sub> B <sub>25</sub>	standard		
14	rectangle	$2 \times 36$	(Co <sub>52</sub> Fe <sub>48</sub> ) <sub>75</sub> B <sub>25</sub>	standard		
15	square	$10 \times 10$	Co <sub>20</sub> Fe <sub>60</sub> B <sub>20</sub>	linear dynamic		
16	rectangle	$2 \times 36$	(Co <sub>52</sub> Fe <sub>48</sub> ) <sub>75</sub> B <sub>25</sub>	standard		
17	rectangle	$2 \times 36$	(Co <sub>52</sub> Fe <sub>48</sub> ) <sub>75</sub> B <sub>25</sub>	standard		
18	square	20  imes 20	Co <sub>20</sub> Fe <sub>60</sub> B <sub>20</sub>	linear dynamic		
19	circle	diameter 30	Co <sub>60</sub> Fe <sub>20</sub> B <sub>20</sub>	linear dynamic		
20	circle	diameter 30	$Co_{60}Fe_{20}B_{20}$	linear dynamic		
21	circle	diameter 30	Co <sub>60</sub> Fe <sub>20</sub> B <sub>20</sub>	linear dynamic		
22	circle	diameter 30	Co <sub>60</sub> Fe <sub>20</sub> B <sub>20</sub>	linear dynamic		
23	circle	diameter 30	Co <sub>60</sub> Fe <sub>20</sub> B <sub>20</sub>	linear dynamic		
24	circle	diameter 30	Co <sub>60</sub> Fe <sub>20</sub> B <sub>20</sub>	linear dynamic		
25	circle	diameter 30	$Co_{60}Fe_{20}B_{20}$	linear dynamic		
26	circle	diameter 60	Co <sub>60</sub> Fe <sub>20</sub> B <sub>20</sub>	linear dynamic		
27	circle	diameter 60	Co <sub>60</sub> Fe <sub>20</sub> B <sub>20</sub>	linear dynamic		
28	circle	diameter 50	$Co_{60}Fe_{20}B_{20}$	linear dynamic		
29	circle	diameter 50	Co <sub>60</sub> Fe <sub>20</sub> B <sub>20</sub>	linear dynamic		
30	circle	diameter 50	Co <sub>60</sub> Fe <sub>20</sub> B <sub>20</sub>	linear dynamic		
31	circle	diameter 50	Co <sub>60</sub> Fe <sub>20</sub> B <sub>20</sub>	linear dynamic		
32	square	$90 \times 90$	$Co_{40}Fe_{40}B_{20}$	linear dynamic		
33	square	90  imes 90	Co <sub>40</sub> Fe <sub>40</sub> B <sub>20</sub>	linear dynamic		
34	square	$100 \times 100$	Co <sub>40</sub> Fe <sub>40</sub> B <sub>20</sub>	linear dynamic		

## References

- 1. Reig, C.; Cardoso de Freitas, S.; Mukhopadhyay, S.C. *Giant Magnetoresistance (GMR) Sensors from Basis to State-of-the-Art Applications;* SSMI 6; Springer: Berlin/Heidelberg, Germany, 2013; pp. 157–180. [CrossRef]
- Loureiro, J.; Fermon, C.; Pannetier-Lecoeur, M.; Arrias, G.; Ferreira, R.; Cardoso, S.; Freitas, P.P. Magnetoresistive detection of magnetic beads flowing at high speed in microfluidic channels. *IEEE Trans. Magn.* 2009, 45, 4873–4876. [CrossRef]
- 3. Cardoso, S.; Leitao, D.C.; Gameiro, L.; Cardoso, F.; Ferreira, R.; Paz, E.; Freitas, P.P. Magnetic tunnel junction sensors with pTesla sensitivity. *Microsyst. Technol.* **2014**, *20*, 793–802. [CrossRef]
- García Vidal, E.; Ramírez Muñoz, D.; Ravelo Arias, S.I.; Sánchez Moreno, J.; Cardoso, S.; Ferreira, R.; Freitas, P.P. Electronic Energy Meter Based on a Tunnel Magnetoresistive Effect (TMR) Current Sensor. *Materials* 2017, 10, 1134. [CrossRef]
- 5. Mazumdar, D.; Liu, X.; Schrag, B.D.; Carter, M.; Shen, W.; Xiao, G. Low frequency noise in highly sensitive magnetic tunnel junctions. *Appl. Phys. Lett.* **2007**, *91*, 033507. [CrossRef]
- 6. Wisniowski, P.; Dabek, M.; Wrona, J. Field noise in tunneling magnetoresistance sensors with variable sensitivity. *Appl. Phys. Lett.* **2015**, *106*, 052404. [CrossRef]

- Egelhoff, W.F., Jr.; Pong, P.W.T.; Unguris, J.; McMichael, R.D.; Nowak, E.R.; Edelstein, A.S.; Burnette, J.E.; Fischer, G.A. Critical challenges for picoTesla magnetic-tunnel-junction sensors. *Sens. Actuators A Phys.* 2009, 155, 217. [CrossRef]
- 8. Lei, Z.Q.; Li, G.J.; Egelhoff, W.F., Jr.; Lai, P.T.; Pong, P.W.T. Review of Noise Sources in Magnetic Tunnel Junction Sensors. *IEEE Tran. Magn.* 2011, 47, 602–612. [CrossRef]
- Mouchel, M.; Bocheux, A.; Ducruet, C.; Sabon, P.; Prejbeanu, I.L.; Conraux, Y.; Alvarez-Herault, J.; Mackay, K.; Baraduc, C. Noise study of magnetic field sensors based on magnetic tunnel junctions. *J. Phys. Conf. Ser.* 2017, 903, 012008. [CrossRef]
- 10. Ingvarsson, S.; Xiao, G.; Parkin, S.S.P.; Gallagher, W.J.; Grinstein, G.; Koch, R.H. Low-frequency magnetic noise in micron-scale magnetic tunnel junctions. *Phys. Rev. Lett.* **2000**, *85*, 3289. [CrossRef] [PubMed]
- Arakawa, T.; Tanaka, T.; Chida, K.; Matsuo, S.; Nishihara, Y.; Chiba, D.; Kobayashi, K.; Ono, T.; Fukushima, A.; Yuasa, S. Low-frequency and shot noises in CoFeB/MgO/CoFeB magnetic tunneling junctions. *Phys. Rev. B* 2012, *86*, 224423. [CrossRef]
- 12. Wisniowski, P.; Dabek, M.; Skowronski, W.; Stobiecki, T.; Cardoso, S.; Freitas, P.P. Reduction of low frequency magnetic noise by voltage-induced magnetic anisotropy modulation in tunneling magnetoresistance sensors. *Appl. Phys. Lett.* **2014**, *105*, 082404. [CrossRef]
- Wisniowski, P.; Dabek, M.; Skowronski, W.; Cardoso, S.; Freitas, P.P. Effect of CoFeB electrode compositions on low frequency magnetic noise in tunneling magnetoresistance sensors. J. Appl. Phys. 2017, 122, 213906. [CrossRef]
- 14. Friedman, J.; Hastie, T.; Tibshirani, R. *The Elements of Statistical Learning*; Springer: New York, NY, USA, 2001; Volume 1. [CrossRef]
- 15. James, G.; Witten, D.; Hastie, T.; Tibshirani, R. *An Introduction to Statistical Learning with Applications in R*; Springer: New York, NY, USA, 2013. [CrossRef]



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