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Prediction of giant magneto impedance on As-cast and post production treated $Fe_{4.3}Co_{68.2}Si_{12.5}B_{15}$ amorphous wires using neural network

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A giant magneto impedance effect was experimentally measured on as-cast and post production treated amorphous wires although it takes some time due to varying measuring condition such as sample, static magnetic field and frequency. Measured data from different as-cast and post production treated samples was used for training of the network. A 3-node input layer, 1-node output layer neural network model with 3 hidden layers and full connectivity between nodes were developed. A total of 1600 input vectors obtained from varied samples were available in the training set. The network was formed by hybrid transfer functions and 21 numbers of nodes in the hidden layers, after the performance of many models were tried. A set of test data, different from the training data set was used to investigate the network performance. The average correlation and prediction error of giant magneto impedance effect were found to be 99% and 1% for tested $Fe_{4.3}Co_{68.2}Si_{12.5}B_{15}$ amorphous wires.

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1. Introduction

A change of high-frequency impedance of very soft ferromagnetic materials is called as giant magneto impedance (GMI) effect. The GMI effect originates in the skin effect as a consequence of the changes in the penetration depth induced by the applied field through modification of the transverse permeability [1,2]. The impedance of an amorphous wire changes strongly with a static magnetic field. The amplitude of the total wire voltage decreases under the influence of a longitudinal field [3]. The GMI effect depends essentially on the interaction between the magnetic field created by the ac current passing through the wire and magnetic domains [4]. Also it varies under the application of annealing, annealing with tension and magnetic field.

The GMI effect can be experimentally on amorphous wires, however it takes some time due to varying measuring condition such as sample, magnetic field and frequency. Recently, artificial neural networks have successfully used for the prediction of magnetic performance in electromagnetic devices made from soft magnetic materials [5]. Therefore, this paper concentrates to predict the GMI effect for amorphous wires using artificial neural network (ANN).

2. Neural network model

A neural network is an interconnected assembly of the simple processing elements, units or nodes, whose functionality is loosely based on the human neuron. The processing ability of the network is stored in the inter-unit connection strengths or weights, obtained by a process of the adaptation to, or learning from, asset of training patterns. Models usually assume that computation is distributed over several processing units, which are interconnected and operate in parallel. Implicit knowledge is built into a neural network by training it. Some neural networks can be trained by being presented with typical input patterns. and the corresponding expected output patterns. The error between the actual and expected output is used to modify the strengths, or weights, of the connections between the neurons. The back-propagation algorithm in Eq.1 [6] is used in this study.

$$\delta_k = \sigma a_k (t_k^p - y_k^p) \tag{1}$$

where a_k , t_k^p , y_k^p , δ_k and σ are neuron k activation, neuron k target pattern, neuron k output pattern, hidden layer neuron k error and output transfer function respectively.

3. Experiment

The main problem with an artificial neural network (ANN) model has been to establish representative training data, particularly when a large number of variables are considered as is in this research.

The previously obtained data from different as-cast and post production treated samples [4] used for the training of the network. A 3-node input layer, 1-node output layer model with 3 hidden layers and full connectivity between nodes were developed. The input parameters were frequency (f), static magnetic field (H), and sample (x) which is as-cast (1), furnace annealed (2), furnace annealed under tension (3), dc current annealed (4) and flash annealed under transverse magnetic field (5) while the output parameter was the GMI effect.

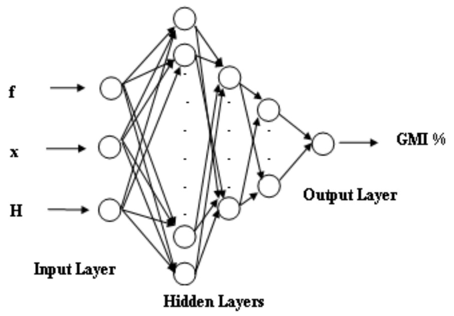

Fig. 1. The developed neural network to predict the GMI effect.

A total of 1600 input vectors obtained from varied samples were available in the training data. The number of hidden layers and neurons in each layer were determined through trial and error to be optimal including with different transfer functions as hyperbolic tangent, sigmoid and hybrid. After the network was trained, a better result was obtained from the network formed by the hyperbolic tangent transfer function in the hidden layer, sigmoid transfer function in output layer and predicted the GMI. The network includes three input neurons, one output neurons, three hidden layers with 30 neurons as shown in Fig.1. A set of the test data, different from the training data set was used to investigate the network performance. 320 vectors for the test data were used to predict

4. Experimental results and discussion

Table 1 compares predictions and measurement of GMI % for $Fe_{77.5}Si_{7.5}B_{15}$ amorphous wires at different frequencies. The average absolute difference for GMI effect is about 1 %.

Table 1. Predicted and measurement GMI %.

f(MHz)	Experimental GMI%	Predicted GMI%
0.5	19.3171	19.3738
1.0	20.6523	19.9125
2.0	25.9875	25.8166
3.0	28.7162	28.8350
4.0	29.6773	29.0623
5.0	37.9290	37.9382
6.0	56.2437	56.1669
7.0	44.8278	44.7110
8.0	42.0042	42.0340
9.0	33.2020	33.4160
10.0	26.9453	26.7837

The average percentage effect to prediction of GMI for sample type, frequency and static magnetic field are 89.2%, 3.94% and 6.06 %, respectively, shown as Fig. 2.

The highest ratio among the input data for affecting the GMI % was found to be sample type which are as-cast, furnace annealed, furnace annealed under tension, dc current annealed and flash annealed under transverse magnetic field amorphous wires.

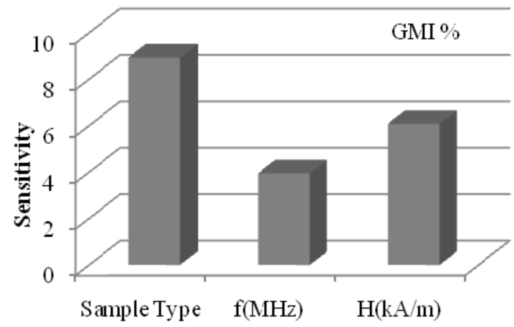

Fig. 2. Effect of input data's on GMI %.

The static magnetic field dependency of the GMI ratio for Co-based amorphous wires at 6 MHz is shown in Fig. 3.

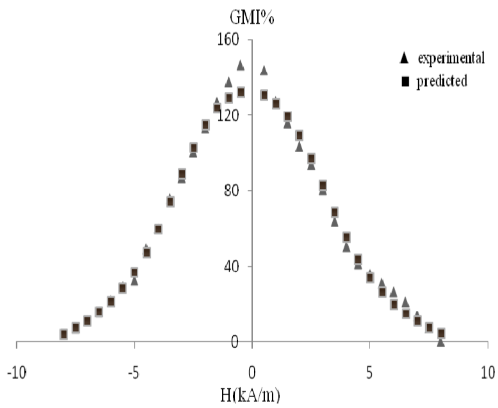

Fig. 3. Correlation between predicted and measured GMI% at 6 MHz.

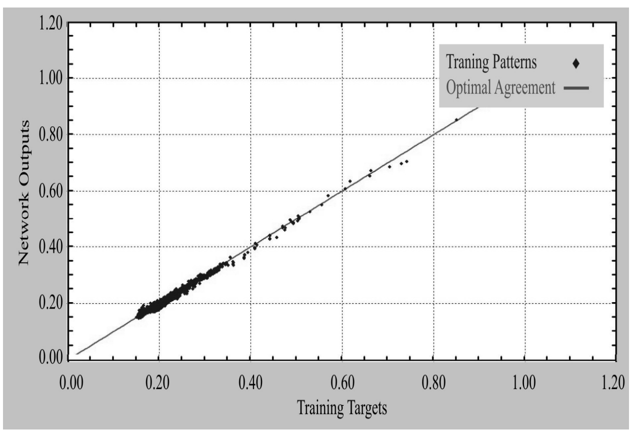

Fig. 4. Correlation of experimental and predicted GMI values.

The static magnetic field dependency of the Fig. 4. also confirms correlation between measured and predicted values.

GMI ratio for Co-based amorphous wires at 6 MHz is shown in Fig. 4.

5. Conclusion

The developed ANN model gives a satisfactory prediction GMI% for the amorphous wires within the range tested. The average correlation and prediction error were found to be 99% and 3% respectively. The model can be improved using expanding the data range. The results have indicated the modelling is a promising tool with potential industrial applications

References

[1] M. Yazici, A. Durmus, A. Bayram, Materialprüfung, **45 5,** 214 (2003)
[2] M. A. Maleque, Y. M. Poon, H. H. Masjuki, J. Mat.Pro. Tech, **153-154** 482-487 (2004).
[3] T. Alp, A. Wazzan, J. Mater. Eng. and Perform. **11,** 351 (2002).
[4] A. Bayram, A. Uguz, M. Ula, Mater. Charact. **43**, 259 (1999).
[5] R. G. Davies, Metall. Trans. *A*, **9**, 671 (1978).
[6] H. C. Cheng, G. H. Cheng, J. Mater. Sci, **24,** 1991 (1989).
[7] M. Sarwar, R. Priestner, J. Mat. Eng. And Per, **83,** 380 (1999).
[8] Y. Tomita, J. Mater. Sci, **25**, 5179 (1990).
[9] M. R. Berrahmoune, S. Berveiller, K. Inal, A. Moulin, E. Patoor Mater. Sci.& Eng. A, **3** (78), 304 (2004).

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