A new formulation for magnetoresistance of electrodeposited CuCoNi alloy films by neural network

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Traditional magnetoresistance formulae used to include differences of resistivity of the samples. However, bath conditions and film constituents were not taken into account. Based on the experimental results, a neural network (NN) model-based explicit formulations were developed to predict the magnetoresistance (MR) of electrodeposited CuCoNi alloys in terms of the amount of film constituents, namely concentrations of Ni in the electrolyte (e), ambient temperature (T), R(0) is the resistance without applying a magnetic field, R(B) is the resistance of sample measured under the applied magnetic field, Nickel content at the film % (Ni), Cupper content at the film % (Cu), Cobalt content at the film % (Co), lattice parameter of the films (a), film thickness (t), and magnetoresistance (MR). The test results have revealed that the film compositions were very effective on the magnetoresistance of electrodeposited alloys. Besides, it was found that the model developed by using NN seemed to have a high prediction capability of magnetoresistance of CuCoNi alloys.

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1. Introduction

In the last decades, a growing interest on the granular alloys composed of magnetic clusters embedded in a metallic matrix has appeared due to the discovering of their giant magnetoresistance (GMR) properties. The GMR was first observed in multilayers of metallic and magnetic layers [1], and than Berkowitz et al. and Xiao et al. [2] observed simultaneously that granular alloys also presented GMR, the origin of it being similar as in the case of the multilayers, that is, the spin scattering of the conducting electrons at the magnetic granules, principally at the interfaces.

Generally, the binary granular alloys with GMR are composed of two immiscible elements. The way of getting a metastable solid solution of both elements is achieved by the use of ultra-rapid quenching techniques such as melt-spinning, laser-ablation, sputtering, etc. Alternatively, electrodeposition technique has been demonstrated useful to prepare Co–Cu-Ni films consisting of a metastable solid solution. Granular thin film systems have the advantage of simplicity of fabrication over the multilayers. Of the various methods available for the preparation of thin films exhibiting GMR, electrodeposition [3] is the simplest and least expensive. Electrodeposition becomes more attractive due to its ability to deposit in geometries where conventional deposition processes would fail.

In an alloy such as thin film, the properties of the constituents and the interactions between them determine the behavior of the material. Several mathematical modeling techniques such as linear/non-linear regression, genetic programming, and neural network (NN) can be attempted to mimic some of the basic physical properties of materials in terms of the film constituents. In recent years, NN models have shown exceptional performance over regression tools and genetic programming, especially when used for the pattern recognition and function estimation. An artificial neural network (ANN), or neural network (NN) for short, utilises interconnected mathematical nodes or neurons to form a network that can model complex functional relationships. The technique is particularly suited to problems that involve the manipulation of multiple parameters and non-linear interpolation, and as a consequence are therefore not easily amenable to conventional theoretical and mathematical approaches. Neural networks have therefore seen growing application in materials property (mechanical and physical) determination, particularly the more difficult to analyze complex multiphase and composite materials, which are growing in popularity.

Guessasma [4] was used the ANN in order to relate milling time, vial and plateau velocities to coercivity, squareness ratio, cubic phase ratio and crystallite size of Co and Co-Ni materials. Scott et. al.[5] showed the possible applicability of NN to estimate the functional properties of ceramic materials. Hamzaoui et.al. [6] was predicted structure and magnetic properties of Fe-Ni alloys over a large range of process parameters.

Altinkok et.al. [7] were predicted using a NN, tensile strength and density and bending strength and hardness [8] of particulate reinforced Al–Si–Mg aluminium matrix composites, and mixture and pore volume fraction in Al2O3/SiC ceramic cake [9].

The magnetoresistance (MR) is defined by the function of $MR = (R(0)-R(B))/R(0)$ where $R(B)$ is the resistance of sample measured under the applied magnetic field and $R(0)$ is the resistance without applying a magnetic field. There is no any study connecting with the film constituents and bath concentration to magnetoresistance. The objective of this paper is to develop a NN model-based explicit formulations to predict the magnetoresistance (MR) of electrodeposited CuCoNi alloys in terms of the amount of film constituents, namely concentrations of Ni in the electrolyte (e), ambient temperature (T), R(0) is the resistance without applying a magnetic field, R(B) is the resistance of sample measured under the applied magnetic field, Nickel content at the film % (Ni), Cupper content at the film % (Cu), Cobalt content at the film % (Co), lattice parameter of the films (a), and film thickness (t).

A ANN was used to quantify the effect of bath conditions (input parameters) on magnetoresistive properties (output parameters) of the electrodeposited CuCoNi alloys.

Electrodeposition of Cu–Co-Ni films was carried out at a constant current density from an aqueous electrolyte of sulfates of Cu, Co and Ni. The experimental details were given our previous study [10].

2. Application of neural network (NN)

2.1. Brief overview of neural network

Neural network is a functional abstraction of the biological neural structures of the central nervous system [11-13]. It can exhibit a surprising number of human brain's characteristics e.g. learn from experience and generalize from previous examples to new problems. In NNs, there are a lot of cells and connections between inputs and outputs. These connections between neurons get a transmission value as for the relation which is called as weight. The weights could be renewed for every new data. After realizing, a present database teaching the system is easily updated with the data to be obtained later [14-16]. The NNs are systems composed of many simple processing elements operating in parallel whose functions are determined primarily by the pattern of connectivity. These systems are capable of high-level functions, such as adaptation or learning, and lower level functions such as data pre-processing for different kinds of inputs. The NNs have been inspired both by biological nervous systems and mathematical theories of learning, information processing, and control.

Neurons are the main processing elements of the NNs. A neuron basically contains three main components namely weights, bias, and activation function. Multi layer perception (MLP) is the basic and commonly used NN model. There are at least three main layers in a MLP which are input, output, and hidden layers. Each neuron in input layer is connected to the neurons in the hidden layer, and there are no connections among the units of the same layer. The number of neurons in each layer may vary depending on the problem. Networks with biases can represent the relationships between the inputs and outputs more easily than the networks without biases [17].

The weighted sum of input components can be calculated by using the Equation 1:

$$Net_j = \sum_{i=1}^{n} w_{ij} * x_i + b \qquad (1)$$

Where x_i represents the input value of i^{th} neuron, w_{ij} represents the weight coefficient between i^{th} and j^{th} neurons, n is the number of input neurons that comes to a cell, b is bias value. Activation function is a function that processes the net input obtained from the sum function and determines the cell output. In this study, tangent-sigmoid transfer function is employed in the proposed NN model. The output of the j^{th} neuron after activation can be evaluated by using the Equation 2:

$$y_i = f(Net_j) = \frac{2}{1+e^{-2U_i}} - 1 \qquad (2)$$

2.2 Data Set

In order to achieve explicit formulations for the magnetoresistance of electrodeposited CuCoNi alloys, experimentally obtained one hundred fourteen test results were used. Film component constituents were employed as the input parameters of the proposed NN model so that the explicit NN based formulations were obtained in terms of concentrations of Ni in the electrolyte (e), ambient temperature (T), R(0) is the resistance without applying a magnetic field, R(B) is the resistance of sample measured under the applied magnetic field, Nickel content at the film % (Ni), Cupper content at the film % (Cu), Cobalt content at the film % (Co), lattice parameter of the films (a), and film thickness (t) contents.

Out of one hundred fourteen experimental results, a set of thirty-one data was used to train the model while the remaining data were involved in testing. The data were randomly selected to generate both the training and testing sets. Magnetoresistances of the CuCoNi alloys were the output of the models developed in the study. The distribution and the ranges of the different input parameters are given in Table 1.

Table 1 Ranges and normalization coefficients of input and output parameters.

Parameters	Lower limit	Upper limit	Normalization coefficient	
			c	D
e	1	40	0.04615	-0.94615
T	23	320	0.006	-1.02
V0	0.086	1.411	1.36363	-1.02272
VB	0.085	1.411	1.36363	-1.02272
Ni	1.564	11.465	0.181634	-1.18335
Cu	66.6	78	0.15789	-11.41578
Co	16.5	31.8	0.11764	-2.84117
a	3.599	3.63	6.0	-216.9
t	1.49	2.433	1.91489	-3.75319
MR	-2.112	0.0708		

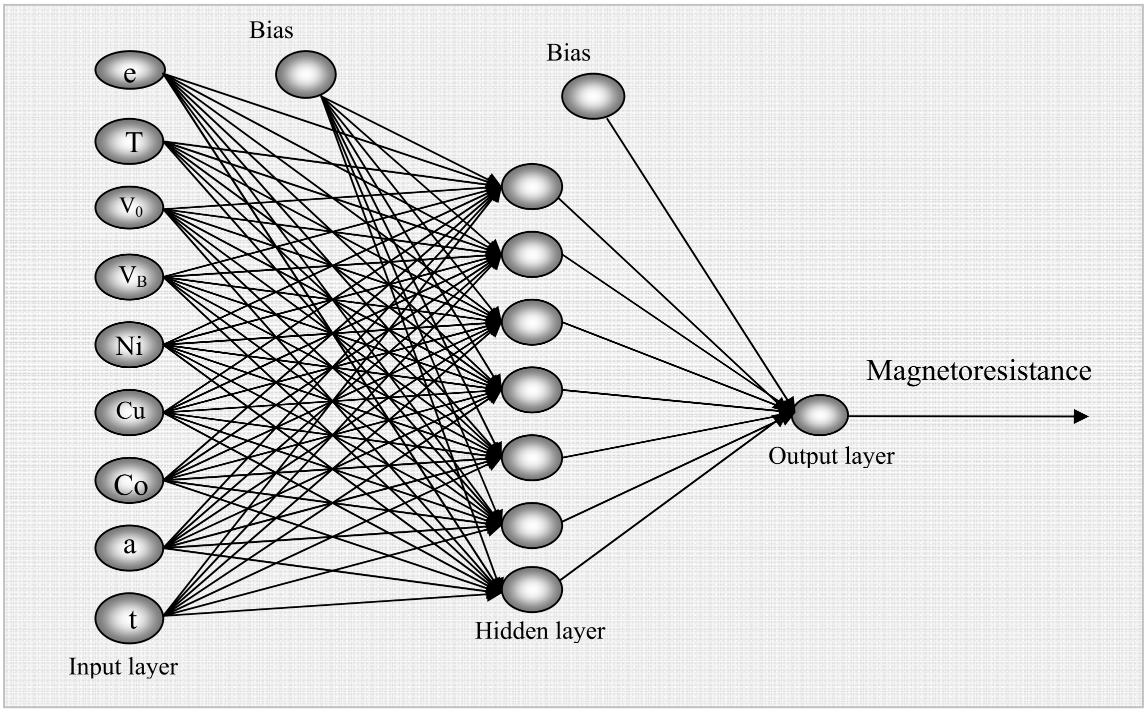

Fig. 1 Neural network model for prediction of magnetoresistance

A 9-7-1 NN architecture as shown in Fig. 1 was adopted to develop the NN model. This architecture indicates that there are nine nodes in the input layer, corresponding to nine factors from nickel content in the electrolyte to film thickness, seven nodes in the hidden layer, and one in the output layer corresponding to the magnetoresistance of CuCoNi alloys.

In order to acquire accurate results from the magnetoresistance to the execution of the training process of the NN, the input and output parameters were normalized in the range of (-0.95; 0.95) via Equation 3:

$$\Gamma_{normalized} = c\Gamma + d \tag{3}$$

where Γ represents parameters used in the NN training process, c and d are normalization coefficients of that particular parameter.

Taking these independent parameters into account, magnetoresistance can functionally be expressed as in Equation 4 as follows:

$$\text{Magnetoresistance} = f(e, T, R(0), R(B), Ni, Cu, Co, a, t) \tag{4}$$

Two different learning algorithms, namely "Conjugate Gradient" and "Levenberg Marquaet" were used in training of the proposed NN model. After training the NN model, it was observed that Levenberg Marquaet gave better statistical results for the present database so that it was chosen as the training algorithm. Thereafter, the input parameters and weights of the trained NN were used to extract explicit expressions. The explicit neural network formulations for the magnetoresistance obtained from the proposed NN model can be expressed as in Equation 5:

$$\text{Magneto resistance} = \left(\left(\frac{2}{1+e^{-2F}} - 1\right) - (0.96176)\right) / (0.88235294) \tag{5}$$

$$\begin{aligned} F = {} & (2.0582) * \left(\frac{2}{1+e^{-2F_1}} - 1\right) + (-1.6176) * \left(\frac{2}{1+e^{-2F_2}} - 1\right) + \\ & (4.20677) * \left(\frac{2}{1+e^{-2F_3}} - 1\right) + (-0.19533) * \left(\frac{2}{1+e^{-2F_4}} - 1\right) + \\ & (2.53952) * \left(\frac{2}{1+e^{-2F_5}} - 1\right) + (-4.2225) * \left(\frac{2}{1+e^{-2F_6}} - 1\right) + (-0.22906) \end{aligned} \tag{5a}$$

$$\begin{aligned} F_1 = {} & (e) * (-0.7138) + (T) * (2.7904) + (V_0) * (-0.3497) + \\ & (V_B) * (-0.9781) + (Ni) * (0.0801) + (Cu) * (-1.2088) + \\ & (Co) * (-0.8823) + (a) * (0.4604) + (t) * (0.0541) + (1.0822) \end{aligned} \tag{5b}$$

$$\begin{aligned} F_2 = {} & (e) * (-0.1278) + (T) * (0.8279) + (V_0) * (-0.2737) + \\ & (V_B) * (-0.227) + (Ni) * (-0.2089) + (Cu) * (0.8339) + \\ & (Co) * (-0.7961) + (a) * (-0.9) + (t) * (-0.674) + (0.8811)) \end{aligned} \tag{5c}$$

$$F_3 = (e)*(-0.5646) + (T)*(3.0849) + (V_0)*(-0.5002) + (V_B)*(-1.0683) + (Ni)*(-0.3604) + (Cu)*(0.3455) + (Co)*(-0.5017) + (a)*(0.0376) + (t)*(-0.3146) + (-1.0635)) \tag{5d}$$

$$F_4 = (e)*(-0.6119) + (T)*(2.9117) + (V_0)*(-0.653) + (V_B)*(-0.8632) + (Ni)*(-0.7793) + (Cu)*(-1.7066) + (Co)*(1.4146) + (a)*(-0.7784) + (t)*(-0.1668) + (1.0774)) \tag{5e}$$

$$F_5 = (e)*(-1.0963) + (T)*(-1.906) + (V_0)*(0.3122) + (V_B)*(0.5254) + (Ni)*(-0.5081) + (Cu)*(-0.7892) + (Co)*(1.623) + (a)*(-0.7868) + (t)*(-0.6389) + (-1.2061)) \tag{5f}$$

$$F_6 = (e)*(-0.1116) + (T)*(1.0279) + (V_0)*(-0.1554) + (V_B)*(0.5404) + (Ni)*(0.081) + (Cu)*(0.777) + (Co)*(-0.7106) + (a)*(-0.1154) + (t)*(-0.0745) + (0.3958)) \tag{5g}$$

$$F_7 = (e)*(0.08309) + (T)*(0.2278) + (V_0)*(-0.2573) + (V_B)*(0.4915) + (Ni)*(-0.1857) + (Cu)*(0.04221) + (Co)*(0.1281) + (a)*(-1.7468) + (t)*(0.6122) + (0.05535)) \tag{5h}$$

2.3 Performance of the proposed models

The performance of the proposed explicit formulation in Equation 5 was plotted in Fig. 2 for training and testing data sets. It was observed that a high prediction capability was achieved for both training and testing data sets even though the latter was not used for the training of the NN. Therefore, the NN appears to have a high generalization capability. The overall performances of sets for formulation in Equations 5 were evaluated via mean square error (MSE), percentage error, and the correlations coefficient (R). As seen in Table 2 that a high coefficient of correlation and a low mean square error were obtained for the training and testing data sets for formulation. The proposed NN models for the magnetoresistance of CuCoNi alloys had correlation coefficients of 0.9907, for training data set, and 0.9901, for the testing data set. Moreover, the mean square error of the magnetoresistance formulation was about 0.003223 and 0.040843 for the training and testing set, respectively. As it is seen these mean square errors are fairly reasonable. Furthermore, the models provided highly reasonable percentage errors of as low as 5.39 % for the training set and 10.48 % for the testing set. Figure 2 also demonstrated that the NN was quite successful in learning the relationship between the different input parameters and the output (Magnetoresistance).

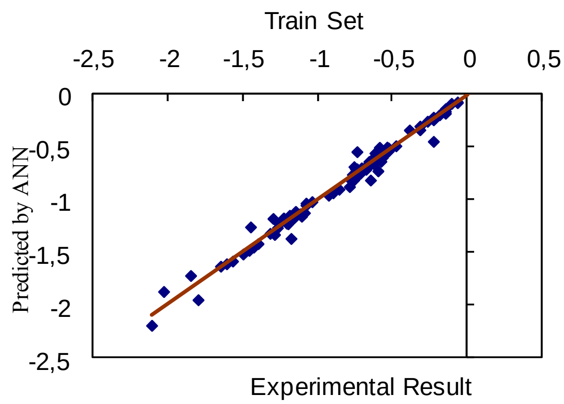

Fig. 2a. Real and calculated wear results of magnetoresistance of electrodeposited CuCoNi alloy films for train set.

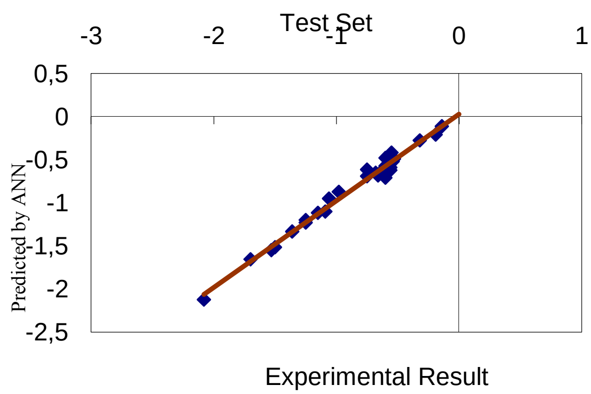

Fig. 2b. Real and calculated wear results of magnetoresistance of electrodeposited CuCoNi alloy films for test set.

Table 2. Statistical performance of the proposed NN model.

Statistical parameter	Train set	Test set
Mean square error (MSE)	0,003223	0,040843
Mean absolute percentage error (MAPE)	5,397904	10,48559
Correlation coeffient (R)	0,9907	0,9901

3. Conclusions

Based on the findings of this study, the following conclusions may be drawn:

- It was found that the models developed by using NN seemed to have a high prediction capability of magnetoresistance of electrodeposited CuCoNi alloys. A high coefficient of correlation and low mean square error values were obtained for the magnetoresistance formulations.

- The proposed NN models for the magnetoresistance had correlation coefficients of 0.9907 for the training data set, and 0.9901 for the testing data set.
- Mean square errors of the MR formulation were 0.003223 and 0.040843 for the training and for the testing sets, respectively. As it is seen, these mean square errors are fairly reasonable.
- The models provided highly reasonable percentage errors of as low as 5.39 % for the training set and 10.48 % for the testing set of magnetoresistance.

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