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PREDICTION OF MAGNETIC PROPERTIES OF STRIP WOUND TOROIDAL CORES UP TO 2 kHz USING ARTIFICIAL NEURAL NETWORK

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Abstract- Although magnetic wound cores have simple geometries, their magnetic properties vary in a complex manner depending on core geometry and dimensions etc. These parameters have a strong influence on magnetic performance of wound toroidal cores made from electrical steels or similar strip products. Through theoretical evaluation and experimental measurements carried out over a few years, magnetic performance of a range of strip wound cores have been quantified at low and high frequency. Using this information a neural network model has been developed for prediction core magnetic field strength, power loss and permeability a wide range of flux density and frequency. Input parameters include variables such as core geometry; dimensions strip width and thickness, induction frequency and flux density. The developed network provides flexibility in the choice of training parameters, transfer functions and training algorithm thereby enhancing accuracy.

Keywords- Magnetic properties, toroidal cores, neural network, electrical steels

1. INTRODUCTION

Strip wound cores made from soft ferromagnetic materials such as SiFe, NiFe and CoFe and newer materials such as amorphous or nano crystalline are increasingly used an alternative to ferrite cores for medium and high frequency applications because of higher magnetic permeability or operating flux density [1]. Thousands of tons of these materials, particularly SiFe are used annually in wound cores for ultimate use in numerous electromagnetic devices. The cores, although they have simple in geometry are subjected to various parameters, which have an influence on their performance such as permeability and the power loss. Predictable and consistent properties are called to avoid rejects and warrant granteed performance. Such consistency has always difficult to achieve because of variability of some parts of manufacturing process such as strip slitting, core winding and bonding. Factors such as these can set up internal stress which seriously affects permeability, internal flux distribution and hence losses [2]. Among other factors affecting magnetic performance of cores, the geometry of wound cores has a profound effect on their magnetic properties [3]. In toroidal cores with an aspect ratio (the ratio of the strip with to built up) from 0.5 to 3.0, the specific power loss can be 20% higher in cores at the low end of the aspect ratio than those at the high end [4]. Because performance of magnetic cores is determined by various distinct parameters of the core and knowledge on the corresponding physical progress is quite restricted, analytical descriptions are extremely difficult making the prediction of relevant characteristics such as specific power loss and permeability by analytical means impractical. Artificial neural networks are increasingly becoming useful in the prediction of magnetic performance of electromagnetic devices [5]. This paper presents an improved artificial neural network model for the prediction of magnetic field strength, specific power loss and permeability of grain oriented 3%SiFe and thin gauge toroidal cores with different geometric size and strip thickness operating up to 2 kHz.

2. THEORY AND MODEL IMPLEMENTATION

A neural network is an interconnected assembly of simple processing elements, units or nodes, those functionally 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 adaptation, to or learning from a set of training patterns. Neural network model usually assume that computation is distributed over several processing units which are interconnected and which operate in parallel. The most popular network is multi-layer perception, which is a feed forward network, i.e., all signals flow in a single direction from input to the output of the network.

Some neural networks can be trained by being presented and corresponding expected output. The error between the actual and expected outputs is used to modify the strengths or weights of the connections between the neurons. This method of training is known as supervised training. In multi-layer perceptions, the back-propagation algorithm for supervised training is often adopted to propagate the error from the output neurons and compute the weight modifications for the neurons in the hidden layers. In an untrained network, an input vector $\vec{X}$ yields an output vector $\vec{Z}$, which usually differs substantially from the target output. The neural network is fed with a series of vectors $\vec{X}$ for which corresponding target $\vec{Z}_T$ has been determined by means of model core experiments. Differences between $\vec{Z}$ and $\vec{Z}_T$ are evaluated in order to modify the weights in a way that reduces the difference iteratively.

For any hidden or output node k,

$$\Delta w_{ki} = \alpha \delta_k x_{ki}^p$$

where hidden nodes

$$\delta_k = \sigma' a_k \sum_{j=I_k} \delta_j w_{jk}$$

and for output nodes

$$\delta_k = \sigma' a_k \left(t_k^p - y_k^p\right)$$

all symbols being as defined in the nomenclature.

A 4-node input layer – 3-node output layer model with 3 hidden layers and full connectivity between nodes was developed. The input parameters were outer diameter, d_0, strip thickness, t, induction frequency, f and the peak value of flux density, B_{max}, when the core magnetised at the flux densities from 50 Hz to 2 kHz under controlled sinusoidal conditions. The output parameters were power loss, P in W/kg, relative permeability, μ_r and the peak value of magnetic field strength, H_{max}. Previous measurements from 5 different combinations of core dimensions over 179 samples with dimensions ranging from 60 to 100 mm outer diameter (d_0), constant 50 mm inside diameter (d_i) and 25 mm strip width (h) and 0.27 mm to 0.08 mm strip thickness (t) and a flux density sweep from 0.2 Tesla to 1.8 Tesla, a total of 1910 input vectors were available in the training set to a back-propagation neural network (Table 1) [6].

A set of 114 cores made from 0.27 mm thick 3%SiFe (M4), 35 and 30 cores made from 0.10 mm and 0.08 mm 3%SiFe thin gauge materials was used in test data respectively. The dimensions of the samples tested was shown in Table 2 and included 12 cores of 0.27 mm 3%SiFe, 6 cores of 0.10 mm thin gauge. The 6 of cores M4 was also used as a training data and others were tested without using in the training data set.

A commercial neural network package has been used for training the networks giving the advantage of rapid network development through flexible choices of algorithms, transfer and output functions and other training parameters, thereby enhancing accuracy. Basically the sigmoid and hyperbolic tangent transfers and output functions with different number of nodes and hidden layers were used and then the results were be able to compared with target data.

Table 1. The sample dimensions in the training set

Diameter (mm)		Strip (mm)	
Outer (d_0)	Inner (d_i)	Width (h)	Thickness (t)
60	50	25	0.27
70	50	25	0.27
80	50	25	0.27
90	50	25	0.27
100	50	25	0.27
60	50	25	0.10
70	50	25	0.10
80	50	25	0.10
90	50	25	0.10
100	50	25	0.10
60	50	25	0.08
70	50	25	0.08
80	50	25	0.08
90	50	25	0.08
100	50	25	0.08

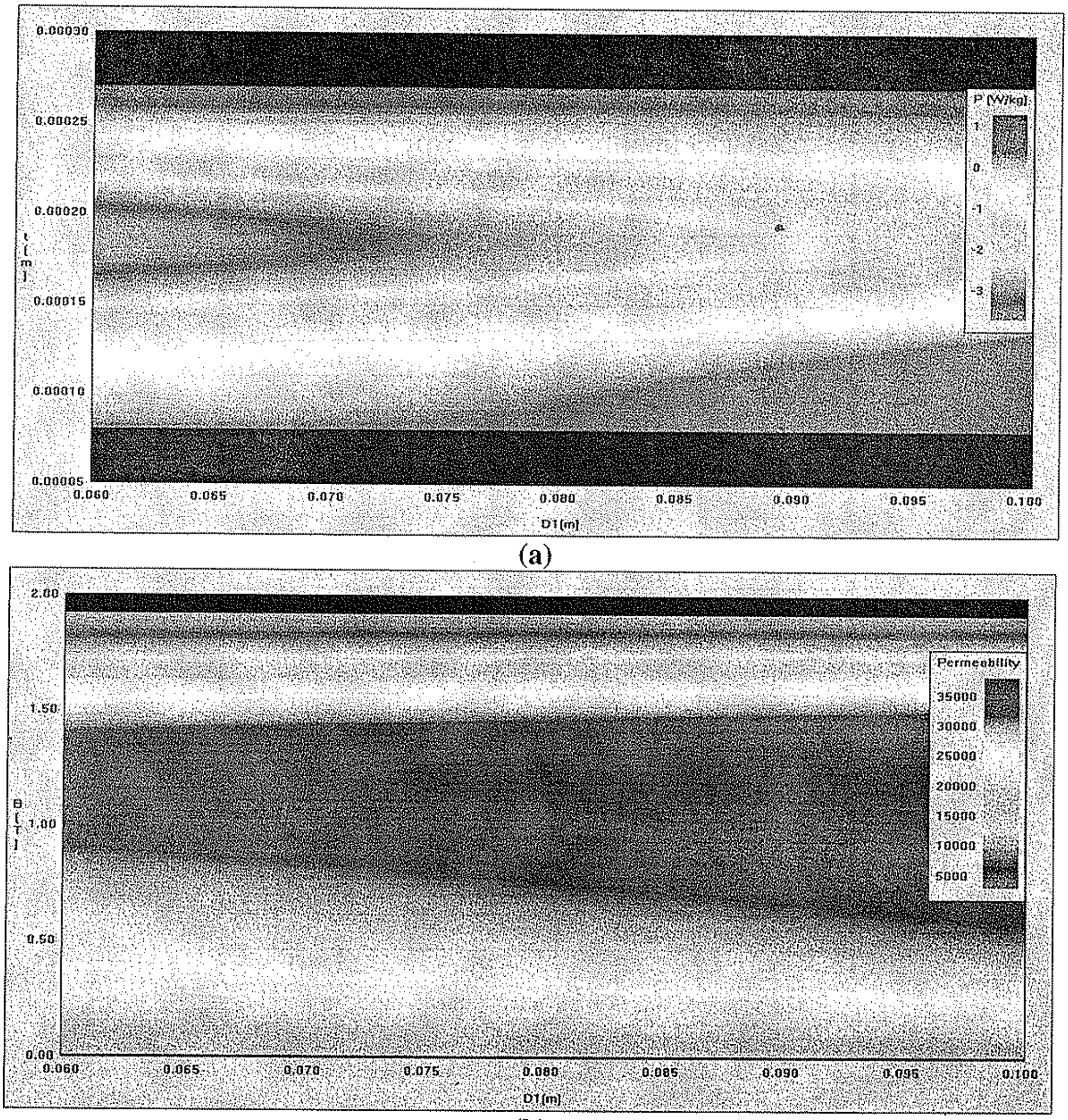
Table 2. The sample dimensions tested

Diameter (mm)		Strip (mm)	
Outer (d_0)	Inner (d_i)	Width (h)	Thickness (t)
80*	50*	25*	0.27*
90	50	25	0.27
80	50	25	0.10

* this sample was also included in the training data set.

3. RESULTS AND DISCUSSION

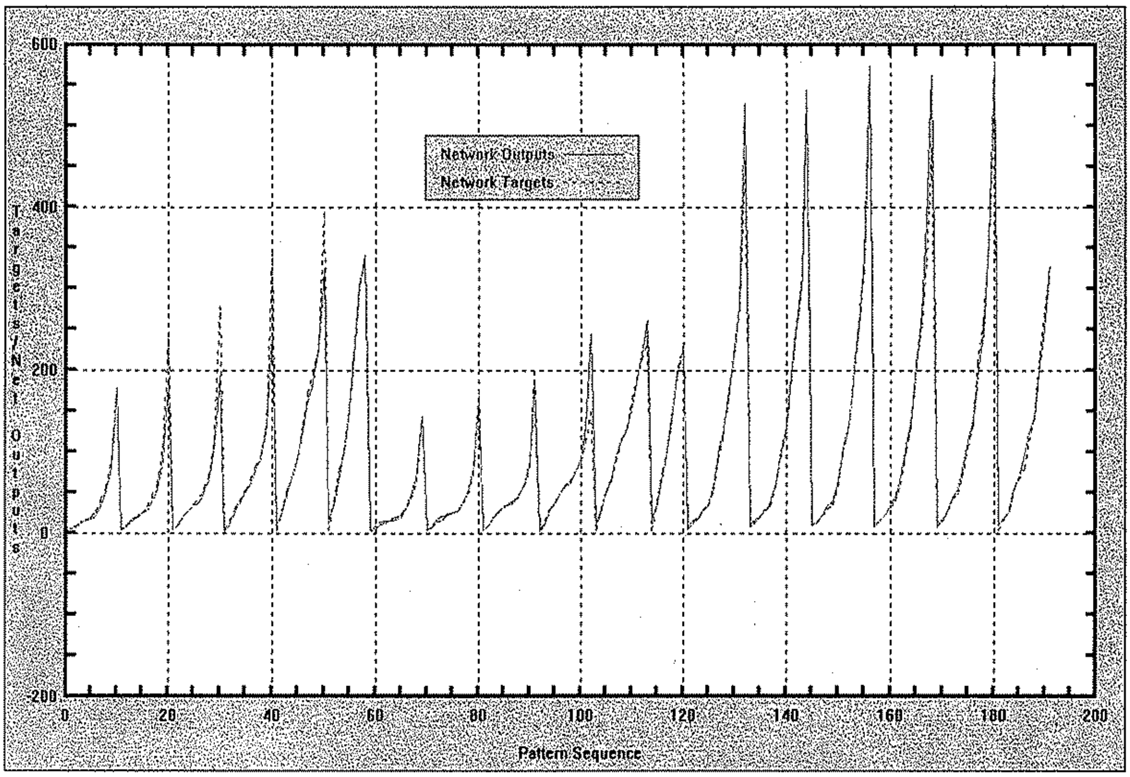
A hybrid (tanh+sigmoid) and sigmoid only models were developed for training. The hybrid model was three kinds according to its hidden and output level transfer functions. The sigmoid only model also included 4 hidden layers. The output results obtained from the networks were similar to each other, however, the 6 level sigmoid type model was used to test the samples. The correlation in this model was 99% in the power loss and permeability and 98% for the magnetic field strength. Figure 1a shows the variation of power loss with strip thickness and outer diameter of the sample M4. Similarly, Figure 1b indicates for the same sample, the effect of flux density and outer diameter on the permeability. All the other parameters in both cases are being kept constant. For a given strip thickness, flux density and outer diameter, the user quickly read the power loss and permeability from the graph. Because of large number of variable parameters involved, a very large volume of these graphs would be have to be produced. Figure 2 shows the network outputs and the network targets on magnetic field strength, power loss and permeability for the cores tested at flux densities 0.2 T and 1.8 T. Figure 3 shows the optimal agreement between the data obtained from the network and measurements.



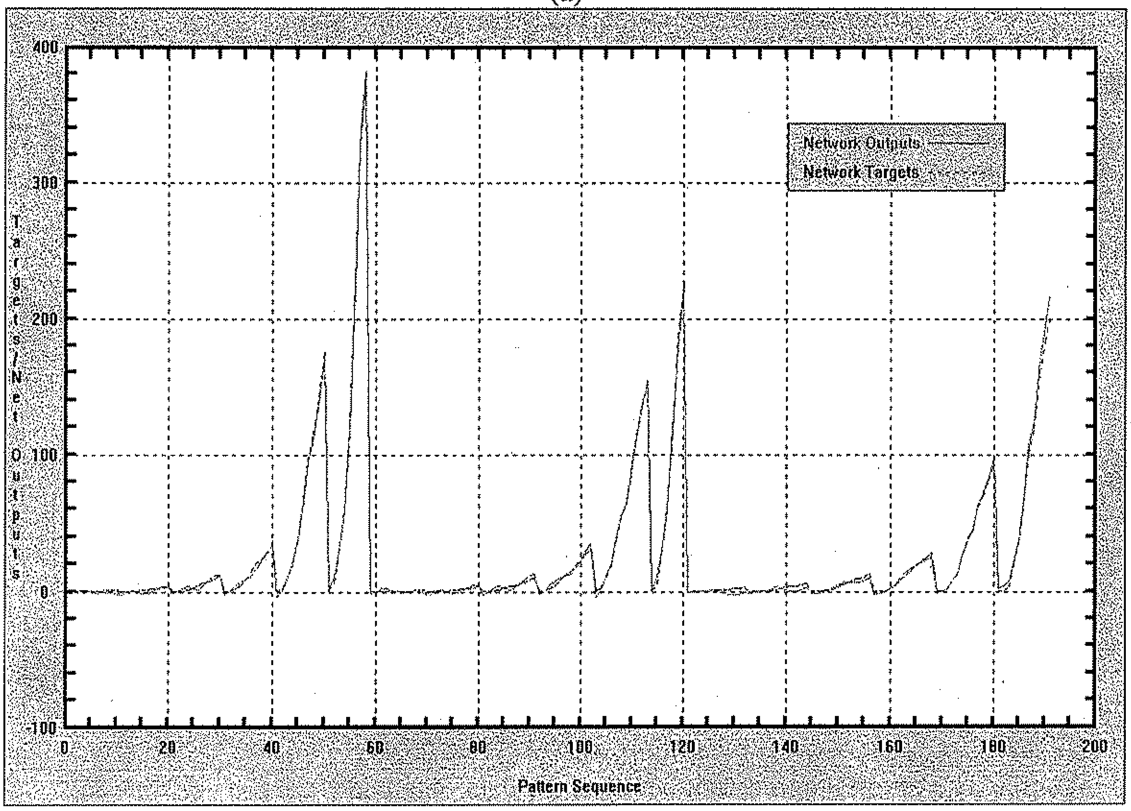
(a)

(b)

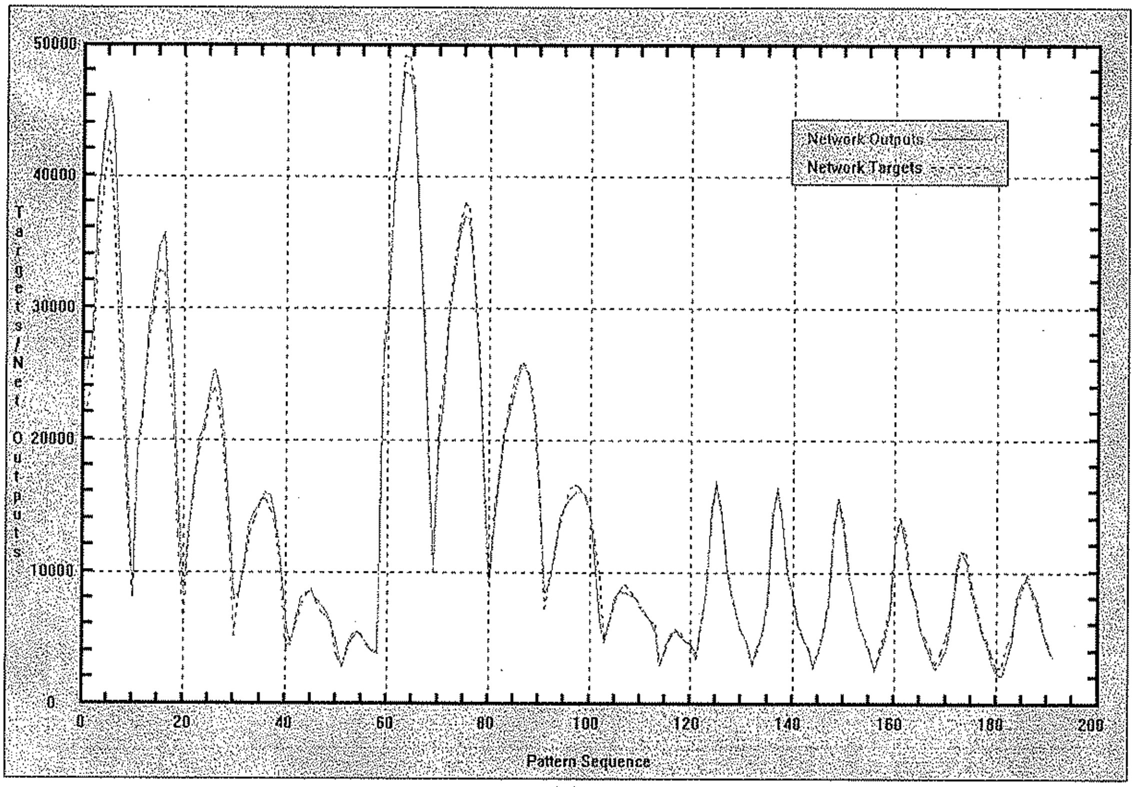
Figure 1. Typical magnetic performance graph after trained (a) effect on power loss, of varying strip thickness and outer diameter and (b) effect on permeability, varying flux density and outer diameter for a M4.toroidal core.


Network Outputs
Network Targets
Targets/Net Outputs
600
400
200
0
-200
0
20
40
60
80
100
120
140
160
180
200
Pattern Sequence

(a)


Network Outputs
Network Targets
Targets/Net Outputs
400
300
200
100
0
-100
0
20
40
60
80
100
120
140
160
180
200
Pattern Sequence

(b)



(c)

Figure 2. The network outputs and network targets on (a) magnetic field strength, (b) power loss and (c) permeability for three test samples.

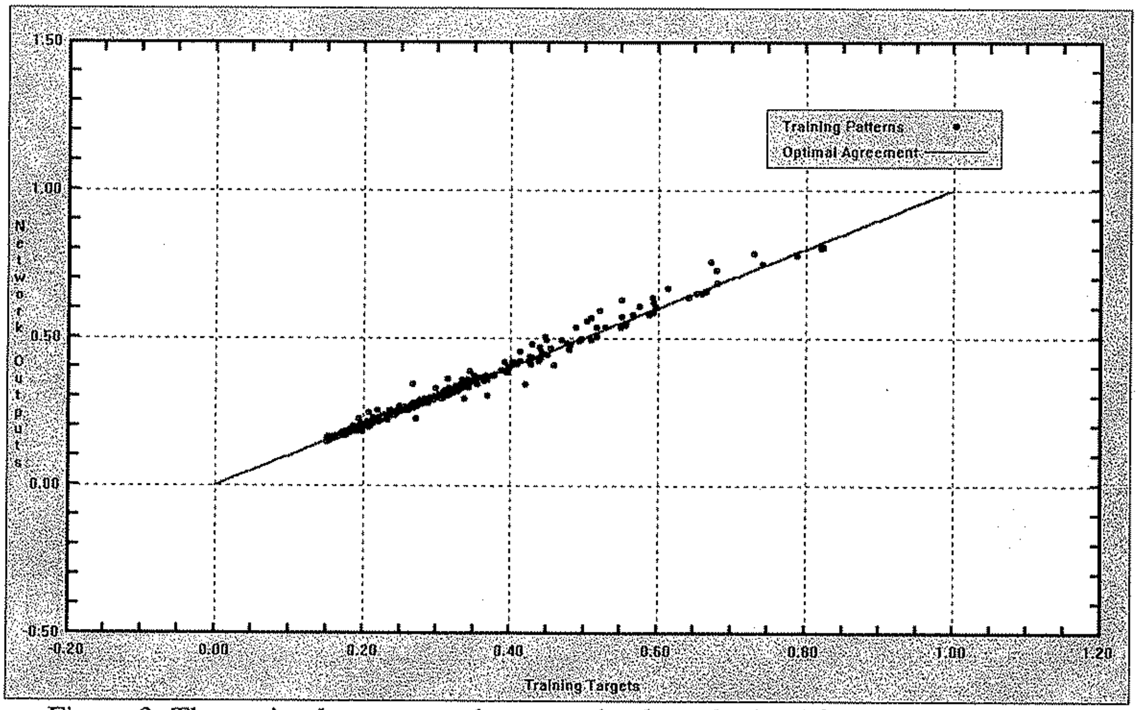


Figure 3. The optimal agreement between the data obtained from the network and measurements for the magnetic field strength, power loss and permeability.

The Figure 2 and Figure 3 show that the target and network output variables are in good agreement, so this model can be used a promising tool to predict magnetic properties on toroidal cores in industrial applications.

4. CONCLUSIONS

A neural network model for the prediction of magnetic properties of strip wound toroidal cores operating up to 2 kHz has been improved. The obtained results are in good agreement between targets and network outputs and they have indicated this to be promising tool with potential industrial application.

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