IRON LOSSES PREDICTION USING NEURAL NETWORK BASED MAGNETIC MODEL

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Abstract - *The possibility to predict the iron losses under nonsinusoidal waveform of magnetic flux density using neural network based magnetic models is analyzed in this paper. Two different types of model structures (predictors with and without feedback) have been used. The predictions are compared to the measured output for different magnetic materials and induction waveforms*
Keywords - iron losses, neural network model.

1. INTRODUCTION

There is little doubt about the technological importance of ferromagnetism today. Huge quantities of electrical power would be impractical without controlled magnetic materials. These materials, used both in electric and electronic equipment, are subject to power losses which may cause, in the case of bad material and/or design, failure in service. To design equipment, it is therefore important to have quantitative knowledge about the total amount of iron losses under different waveform of magnetic flux density. In evaluating the iron losses under nonsinusoidal magnetic induction waveform most attempts were made by analyzing the effects of the upper harmonics from the frequency spectrum of the magnetic flux density [1], [2], [3]. It results accurate but difficult to evaluate formulas. Moreover, the experimental setup and procedure can be cumbersome because small errors made in the determination of the frequency spectrum may cause large errors in power loss calculation [4]. A different way to estimate these losses is proposed in this paper. A multilayer perceptron type neural network is used in order to predict the shape of the dynamic hysteresis loop and, by consequence, the iron losses.

2. MODELING THE MAGNETIC HYSTERESIS

Most simulation codes solve electromagnetic problems taking into consideration a direct relationship between magnetic flux ***B*** and magnetic field ***H***:

$$B=f(H) \tag{1}$$

with f as a monotonic continuous function. This kind of material laws cannot describe history dependence phenomena like the well-known magnetization hysteresis loop. Thus, they are applicable only in cases of monotonic magnetization. To describe the behavior of magnetic materials under nonmonotonic magnetic field conditions, models were developed incorporating history dependent material properties [5],[6], using spin up and down or using analytical functions, respectively [7]. It is the case, for example, of the Preisach type model, which assumed that each of domains has a rectangular hysteresis loop and interaction between domains can be introduced by assuming local field acting on domains, and of the Chua type model, which is based on the fact that a trajectory of flux linkage versus current is uniquely determined by the last point at which the time derivative of flux linkage change sign. In addition, the concept of internal variables known from the field of irreversible thermodynamics and established in phenomenological modelling of inelastic mechanical behaviour of solids has been proposed as a suitable framework for formulating models describing magnetic hysteresis behaviour [8]. In the past decade great interest was paid to the artificial neural network regarded as tools suitable for the presentation of complex , functional relationships necessary for nonlinear system modelling and identification. The information is distributed to the neurons of a network and stored in weighting factors. Artificial neural networks can be trained to learn specific behaviour and are hence suitable as universal modules wherever complex behaviour has to be described. Many neural network based model for the hysteresis phenomenon have been proposed. Some authors [9] even have developed networks which contain the Preisach memory mechanism, or Preisach models of magnetic materials. This paper emphasis some results obtained using dynamic NN.

3. NEURAL NETWORK BASED MAGNETIC MODEL

3.1 Dynamic multi-layer perceptron networks

Usually the mapping task from a domain of input space to the output space, performed by a neural network is called static (spatial) if there is no time-dependency involved in the mapping action. However, dynamic systems can be considered as spatiotemporal mapping rules which involves the time as a model parameter. Recently, several approaches have been proposed to introduce dynamics to NN. Such neural networks can be essentially classified according to the realization of the dynamic character as:

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- NN with lumped dynamics (or time delayed NN) which provide a static NN with delayed measurements of the process input and output. Accordingly, the network approximates the current system output as a function of the delayed measurements;
- Recurrent neural network (RNN) which posses a long-term memory through recurrent connections within the network;
- Neural network with locally distributed dynamics (LDNN) which can be essentially be considered as locally recurrent networks with globally feed forward information processing.

3.2 Model structure selection

Two types of dynamic NN have been compared in order to find a good model for the hysteresis phenomenon [10]. The first choice was a NN with lumped dynamics. Let us make the NARX assumption for the system. A feedforward neural predictor (2) will therefore be used:

$$B_p(k+1) = \varphi(B(k),...B(k-n+1), H(k),...H(k-m+1);\theta) \quad (2)$$

The predicted value of induction B_p is computed using *n* past outputs and *m* past inputs. Fig.1. shows a possible implementation of predictor (2) where the function φ is computed by a fully connected feedforward network with weights θ.

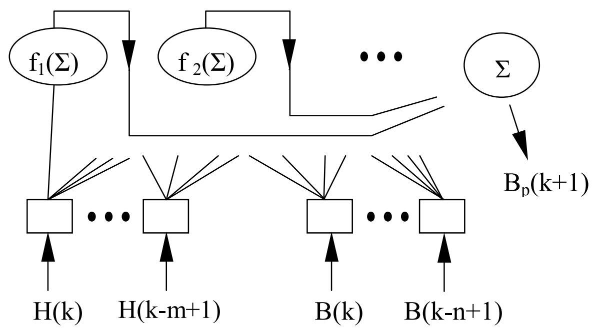

Fig.1 – Neural NARX predictor

A second attempt was made using a neural NOE predictor. This one has feedback through the choice of regressors (*n* past predicted outputs and *m* past inputs) so it can be considered as a recurrent neural network model.

Slightly better results have been obtained with NARX predictor so further on in this paper we will refer to this neural model. It was implemented with a multilayer perceptron network which have one hidden layer (seven hidden units with hyperbolic tangent activation function). The output neuron has a linear activation function.

3.3 Experimental set-up

Special attention was paid to the experimental set-up and measuring procedure used to acquire data both for training and testing the network. The input-output sets must reflect the two major properties of magnetic materials behaviour:

- The saturation effect;
- The rate-dependent and also amplitude-dependent hysteretic character.

Taking into account also that the input training and input test sequences must be significantly different one from another, the following (Fig.2) waveform of magnetic field intensity have been chosen. Note that in Fig.2 the normalized values are represented.

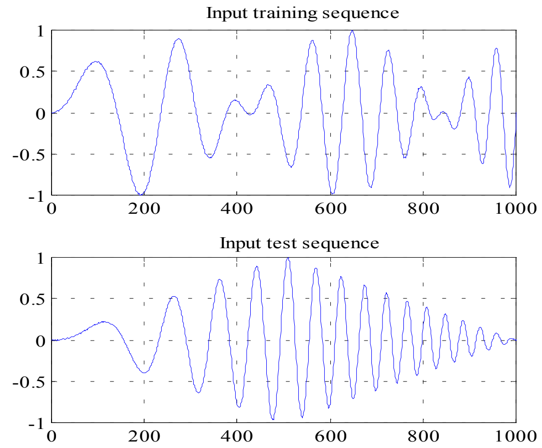

Fig.2 – Normalized value of magnetic field intensity (training and test sequences)

The central frequency value is for both waveforms 50 Hz. The first one is covering frequencies from 30 to 160 Hz (sine modulated) and the second one from 25 to 250 Hz (triangle modulated). Using a standard (IEC 404-10) Epstein frame, several materials have been analysed, including Fe-Si (with and without oriented grains) and FeNi alloy. Experimental data were collected with AT-MIO 16E10 DAQ through LabView graphical programming language and passed to Matlab environment for processing.

3.4 Model identification

The first step in model identification consist in determining the order of the system from the input-output test sequences. It is sometimes difficult to evaluate this one from experimental data but it gives us the necessary information about the number of the regresors used as inputs nodes in the neural network. The results obtained in investigating system orders from 1 to 4 for a grain oriented electrical steel are presented in Fig.3.

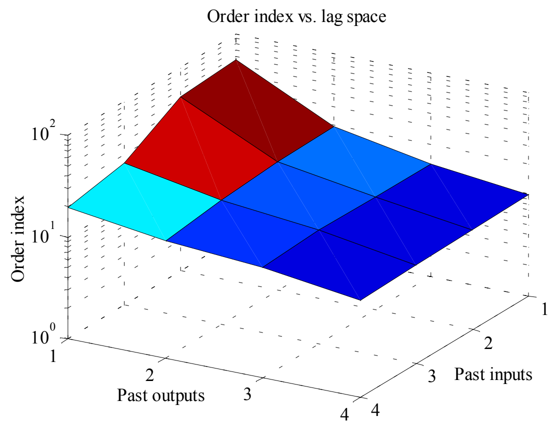

Fig.3 – Order index for a grain oriented FeSi alloy

Nothing certain can be concluded from Fig.3 the reason being probably the noise which is corrupting the measurements. However it is reasonable to assume that the system can be modelled using a number of two past outputs and one past input since the slope is decreasing for a greater number of regressors. Several other input-output sequences of different shapes reveals a similar behaviour. But it is only the case of the above mentioned magnetic material. For other materials the number of regressors can be significantly different. For example, a FeNi alloy can be modelled using four past outputs and two past inputs. However all of the analysed materials have something in common. The number of past outputs is always greater than the number of past inputs. This means that the magnetic history prevail over the magnetic field changes.

As mentioned above a multi-layer perceptron with one hidden layer (seven hidden units with hyperbolic tangent activation function) was used in order to build the NARX predictor. After the training procedure, the input test sequence has been applied to the trained network and the predicted values of the output have been compared with the experimental ones. The results are presented in Fig.4.

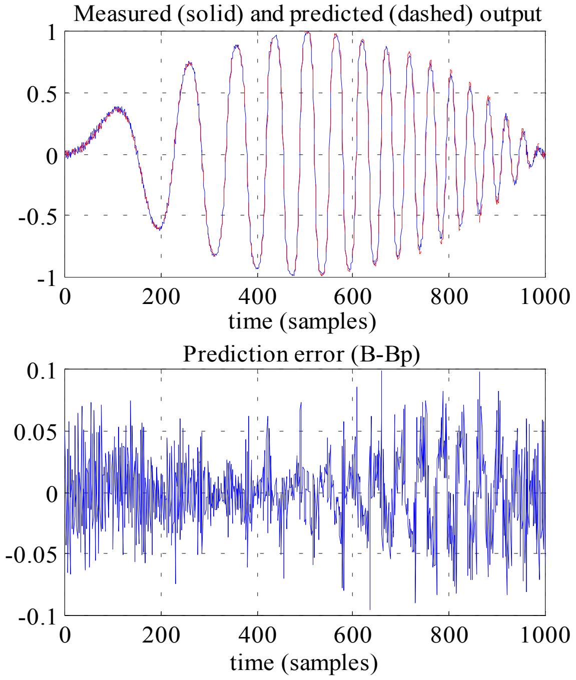

Fig.4 – Measured and predicted values of magnetic flux density (test sequence performed with the trained network)

As depicted in Fig.4, the measured and predicted values of magnetic flux density (normalized values) are relatively closed one to another. One of the most common ways of validating an estimated model, inspirated from linear system identification, is to evaluate the auto correlation function of the residuals and the cross correlation function between input and residuals. The results obtained are presented in Fig.5.

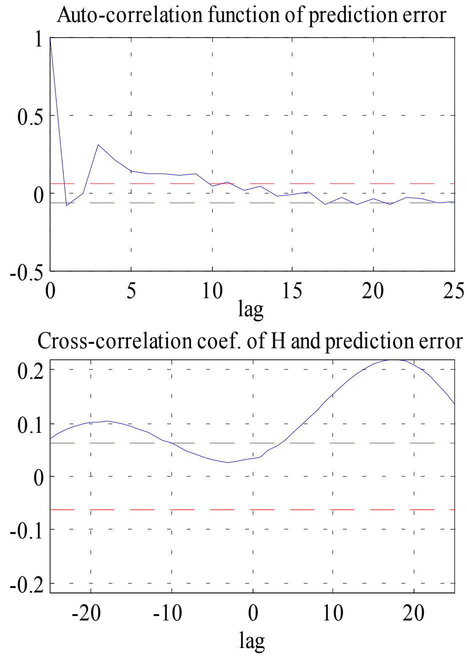

Fig.5 – Residual functions associated with the model

One can observe that the 99% confidence limits are generally exceeded which is not the case for the training input-output sequences. This one usually happens when the network is overfitting the data (the model structure contains too many weights). One of the most powerful method in improving the network performances is to remove the unnecessary weights from the network according to the Optimal Brain Surgeon strategy [11]. In Fig.6 are represented the auto-correlation and cross-correlation functions for the optimised model.

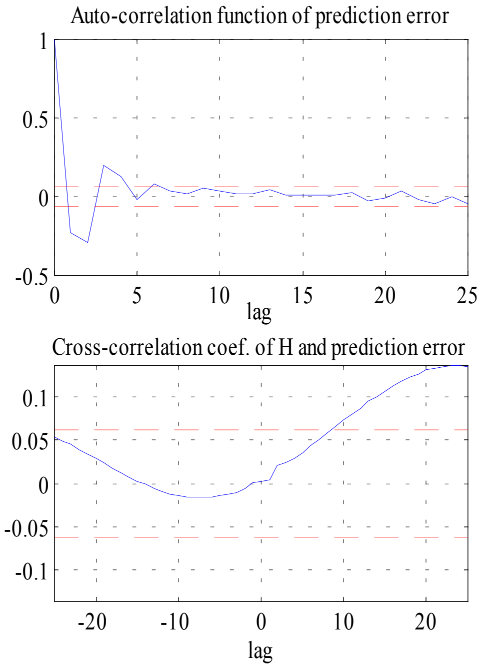

Fig.6 – Residual functions associated with the optimized model

The optimal structure of the network, determined by pruning is represented in Fig. 7.

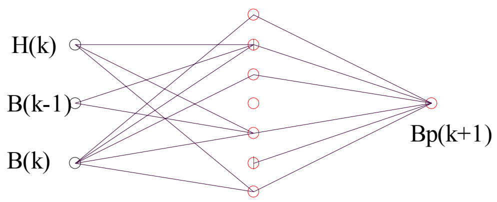

Fig.7 – Optimal network architecture

It is clear now that only six units are necessary in the hidden layer of the network.

3.5 Iron losses prediction

Using the optimised neural network, iron losses can be evaluated by numerically integrating the dynamic hysteresis loop. The predictions of the NARX model compared to the measured values are represented, in terms of maximum relative error, in Table I. The evaluations have been done for FeSi and FeNi alloys under sinusoidal (50 Hz) and nonsinusoidal (50 Hz with third and fifth harmonic)

Table I – Relative errors of predicted iron losses.

	FeSi		FeNi	
	Max. relative error [%]	Conditions	Max. relative error [%]	Conditions
50 Hz	2.71	B_m=0.4 T	3.49	B_m=0.2 T
50 + 150 Hz	2.35	B_{m3}/B_m=0.15	5.10	B_{m3}/B_m=0.1
50 + 250 Hz	4.19	B_{m5}/B_m=0.1	4.23	B_{m5}/B_m=0.1

These results confirm that neural network based magnetic model is a powerful tool in investigating the iron losses.

4. CONCLUSIONS

The behavior of magnetic materials under nonsinusoidal magnetization steady state can be successfully modeled using NARX and NOE models implemented with multilayer perceptron neural networks. Consequently , the total amount of iron losses can be predicted with high accuracy.

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