12th IMEKO TC4 International Symposium
Electrical Measurements and Instrumentation
September 25–27, 2002, Zagreb, Croatia

FUZZY VERSUS NEURAL NETWORK MAGNETIC MODEL IN IRON LOSSES PREDICTION

Marinel Temneanu, Traian Balan, Dana Balan, Cristina Temneanu

Faculty of Electrical Engineering, Technical University "Gh. Asachi" of Iasi, Romania

Abstract − This paper emphasis the possibility to use both fuzzy and neural network based magnetic models in the prediction of the iron losses. The predictions are compared to the measured output for different magnetic materials and induction waveforms. Comparable results have been obtained proving the capacity of both techniques to describe the complex magnetic behavior of the materials being tested.

Keywords: Fuzzy, neural network, magnetic model.

1. INTRODUCTION

Magnetic materials, used 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. Being the interest of both industrial and academic research units, the prediction of iron losses has become the research subject of several multinational networks (see for example [1]). The involved phenomenon is very complex and therefore the practical approach is strongly dependent on the specificity of the magnetization regime. For a sinusoidal waveform of magnetic flux density the evaluation is usually done by using the specific loss data sheet provided by the material manufacturer, the only needed parameters being the frequency and the peak value of the induction in magnetic material. If the magnetization is a nonsinusoidal one the data sheet can still be used (knowing the frequency spectrum of induction) but the results are affected by large relative errors. In these cases two other techniques have been developed. The first one is addressing the iron losses with formulas describing each component (static, classic and excess loses) on the basis of time variation of magnetic induction [2]. The second one is assuming that a magnetic model can be identified from the experimental results and then the total losses can be calculated using their integral definition form. This last approach has recently result in many magnetic models some of them being included in computer aided design software used as a tool to predict the behavior of different electric equipments.

2. MODELS OF HYSTERESIS

Many mathematical approaches have been proposed in order to solve the problem of modeling the magnetic behavior of materials under simple or more complicated supply conditions. All of them are well defined for a specific geometric structure and there are reports on :

- simulation codes solving electromagnetic problems taking into consideration a direct monotonic continuous relationship between magnetic flux B and magnetic field H;
- models incorporating history dependent material properties [3],[4];
- models using spin up and down or using analytical functions, respectively [5];
- models implementing the concept of internal variables known from the field of irreversible thermodynamics and established in phenomenological modeling of inelastic mechanical behavior of solids [6].

Last decade can be characterized as the "upgrading decade" since most of the classic approaches have been combined with the Artificial Intelligence algorithms in order to result in more accurate magnetic models, [7]. Three of the AI components have been extensively used:

- artificial neural networks;
- fuzzy systems;
- genetic algorithms.

Artificial neural networks and fuzzy systems share a common objective: to emulate the operation of the human brain. In some sense, artificial neural networks try to emulate the hardware structure of the human brain – a massive connection of a huge number of simple neurons - while the fuzzy systems try to emulate our brain from a higher-level input-output point of view. Since most of the research conducted until today have been concentrated on implementing the AI techniques into the classic magnetic modeling framework, this paper is addressing two types of magnetic models (neural network and fuzzy system based) from a systemic point of view.

3. EXPERIMENT DESIGN

3.1. Input selection

As pointed before, the magnetic material is treated further on as a dynamic system and the objective is to find a suitable fuzzy model for its behavior. The first and probably the most important thing to do is to extract as much information as possible by using appropriate input signal. For linear systems a square input with random duty cycle gives maximal variance but for non-linear systems amplitude is also important and for this reason the experiments should involve as many amplitudes as possible. This signal must reveal all the important properties of the system being tested. In our case it must expose the saturation effect, the rate dependent hysteretic character and also the minor (second order) loops. Most authors [9] are suggesting the swept sinus with random frequencies as best candidate. In practice it is very difficult to obtain and control such signals so two other inputs (Fig.1) have been used (the same as in [8])

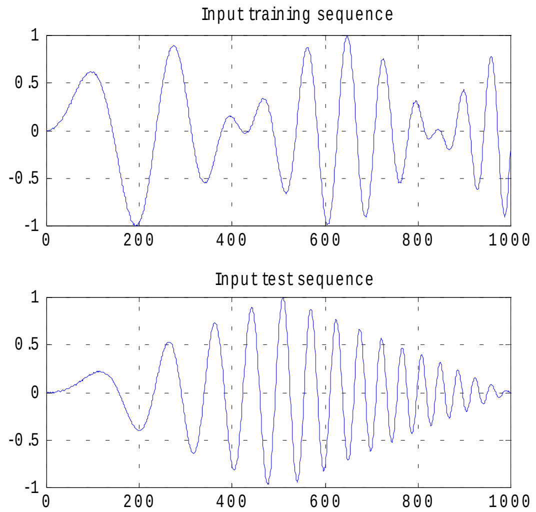

Fig.1 – Normalized value of magnetic field intensity (training and test sequences)

The central frequency value for the training sequence is 50 Hz and it is covering frequencies in the range 30-160 Hz (sine modulated). In order to test the identified fuzzy model a different shape was selected for the test sequence (central frequency – 50Hz, frequencies in 25-250 range, triangle modulation).

3.2. Choosing the structure and the regressors

The following structures are usually used in non-linear modeling:

- NFIR models – the vector of regressors is composed only on past inputs;
- NARX models – the vector of regresors has past inputs and past outputs;
- NOE models – the vector of regressors has past inputs and past estimated outputs;
- NARMAX models – as regressors past inputs , past outputs and estimation error are used.

A NARX assumption was used as describing the magnetic behavior and there are several reasons for this choice:

- It is easy to estimate due to the fact that its structure is non-recursive;
- The procedures that involve fuzzy clustering can only be applied on NARX models;
- We intend to compare the results with those reported in [8] where a neural network based NARX structure was used.

The predicted value of magnetic field density B_p is computed using *n* past outputs and *m* past inputs.

Choosing the right number of regressors is the next important step but, unfortunately, there are no easy and also secure methods to do this. For the case of fuzzy models Sugeno and Yasukawa suggest the use of the so-called regularity criterion (RC) combined with a search tree in order to find the inputs of the model but this search is not very efficient because the parameters of the model has to be calculated every time a candidate regressor is tested. Usually if the input signal has a signal to noise ratio greater than 10 dB another method [9] based on the evaluation of the Lipschitz quotients is used.

3.3. Fuzzy model identification and validation

Once the structure and the regressors being established another choice has to be done for the fuzzy model type - Mamdani or Takagi-Sugeno. The first one is a linguistic model describing a given system by means of linguistic if-then rules with fuzzy proposition in the antecedent as well as in the consequent. The Takagi–Sugeno (TS) fuzzy model on the other hand, uses crisp functions in the consequents. The choice is to be made based on the available sources of information for building fuzzy models: prior knowledge and/or data (process measurements). An important aspect here is the purpose of modeling. Following, the number, type and distribution of membership functions for each variable has to be established. This choice determines the level of granularity of the model. Again, the purpose of modeling and the detail of available knowledge, will influence this choice. Automated, data-driven methods can be used to add or remove membership functions from the model. After the structure is fixed, including here the inference mechanism, the operators and the defuzzification method, the performance of a fuzzy model can be fine-tuned by adjusting its parameters. Tunable parameters are the parameters of antecedent and consequent membership functions (determine their shape and position) and the rules. It ends with the model validation usually done by estimating the prediction error.

4. EXPERIMENTAL RESULTS

In order to obtain the relevant data a classic experimental set-up has been arranged. It contains a signal generator (Tektronix AFG310) followed by a power amplifier provided with a magnetizing current feedback. Two types of magnetic materials, grain oriented FeSi alloy and FeNi alloy have been tested in a standard 25 cm. Epstein frame (IEC 404-10). The data were collected with an AT-MIO 16E-10 DAQ board using a virtual magnetometer (LabView based) and processed in Matlab. As mentioned before, in order to compare the results with those obtained by neural network based modeling [8], a NARX predictor has been used, the vector of regressors being composed on two past outputs and one past input. Because of the large amount of data available, a Takagi-Sugeno fuzzy model was selected. Two software toolboxes, specially conceived for fuzzy modelling and identification have been used, Fuzzy Modeling and Identification Toolbox v303 [10] and Fuzzy Logic Toolbox v2 for Matlab developed by J-S Jang.

The first one build MIMO input-output static or dynamic fuzzy model from data by means of product-space clustering using the Gustafson-Kessel algorithm. The second one was

used to build and identify neuro-fuzzy model with the so-called neuro-adaptive learning techniques incorporated into ANFIS in this toolbox.
The results obtained in modeling the behavior of grain oriented FeSi alloy are presented in Fig. 2. and Fig 3.

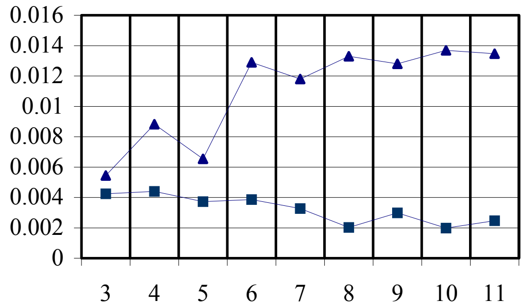

Fig. 2. Average prediction error on training sequence obtained with FMID (triangular markers) and ANFIS (squared markers)

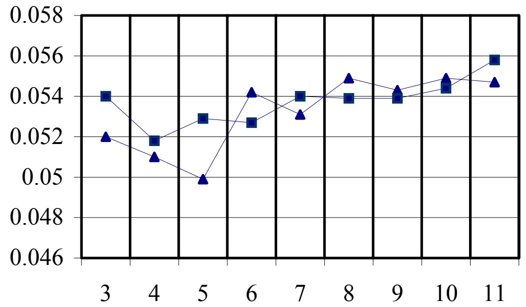

Fig. 3. Average prediction error on test sequence obtained with FMID (triangular markers) and ANFIS (squared markers)

It is remarkable that the average prediction error for both models remains at very low levels for the training and also for the test sequences. It can also be observed that the accuracy is maintained even if a small number of clusters (rules) are used. Moreover, a slightly improvement in prediction precision may be observed in these cases. For this reason further improvements have been tested only on the model that is using only 5 clusters with the structure depicted in Fig.4

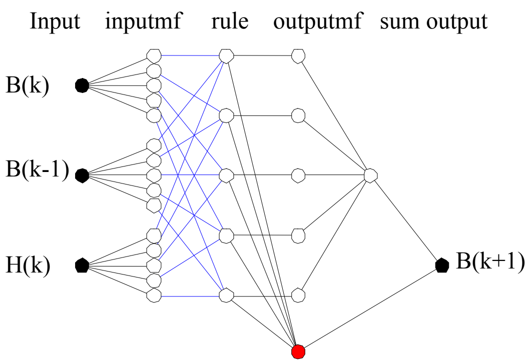

Fig. 4. Fuzzy model structure – 5 clusters before reduction

The rules obtained by tuning the parameters of the fuzzy model is presented in Table 1.

Table 1. Consequent parameters

rule	B(k)	B(k-1)	H(k)	offset
1	$2.05 \cdot 10^{0}$	$-1.16 \cdot 10^{0}$	$1.03 \cdot 10^{-1}$	$-2.48 \cdot 10^{-2}$
2	$2.00 \cdot 10^{0}$	$-1.03 \cdot 10^{0}$	$3.25 \cdot 10^{-2}$	$6.11 \cdot 10^{-4}$
3	$2.02 \cdot 10^{0}$	$-1.29 \cdot 10^{0}$	$4.43 \cdot 10^{-1}$	$2.22 \cdot 10^{-6}$
4	$2.02 \cdot 10^{0}$	$-1.22 \cdot 10^{0}$	$3.20 \cdot 10^{-1}$	$1.28 \cdot 10^{-3}$
5	$2.03 \cdot 10^{0}$	$-1.08 \cdot 10^{0}$	$3.83 \cdot 10^{-2}$	$1.15 \cdot 10^{-2}$

Every time when a model is identified it arise a new problem. Is this the best solution or it can be done more?
For the fuzzy models the next step is to simplify and reduce the model by merging by merging similar fuzzy sets and removing fuzzy sets similar to the universal one. Let's take a look at the membership functions for the three inputs (Fig.5)

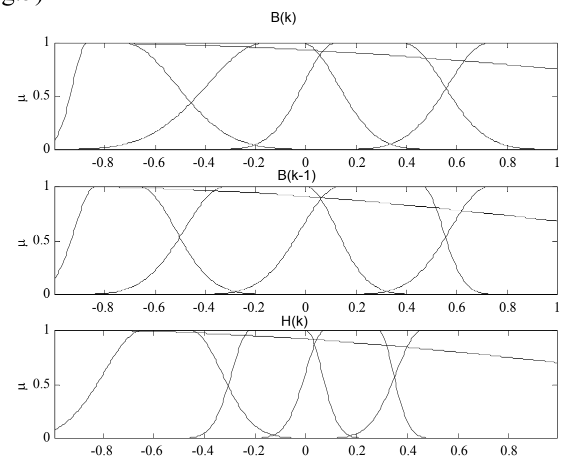

Fig. 5. Membership functions for the three inputs

The partition obtained by clustering the data look a little strange. There are no similar fuzzy sets but it is a set, in all three inputs memberships, which is very close to the universal one. There are powerful algorithms used for fuzzy model reduction but the results are not always acceptable. One of these, available in FMID Toolbox, was used for our model. The resulted structure is presented in Fig. 6 and the membership function for the remaining inputs in Fig. 7.

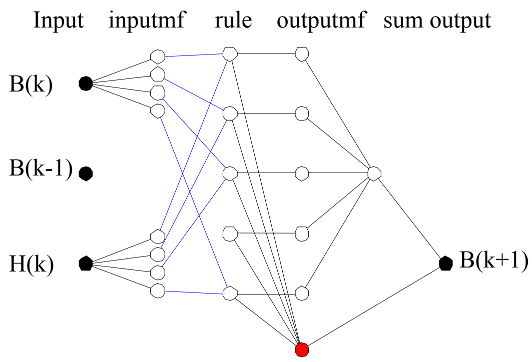

Fig. 6. Fuzzy model structure – 5 clusters after reduction

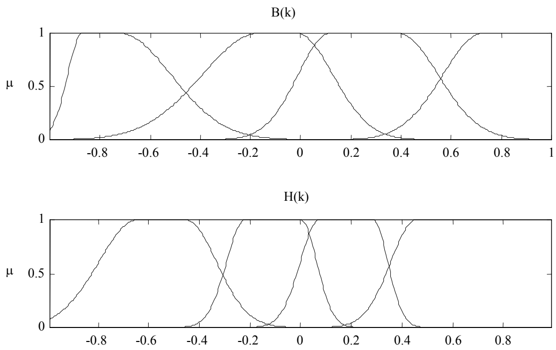

Fig. 5. Membership functions for the remaining two inputs

It is obvious that only 4 clusters remains and the partition look better, in terms of linguistic interpretation. Even the rules are simplified.

The surprise arrived from the fact that one input has been completely removed, only one past input and one past output being used to predict the next value of magnetic field density. The payoff for this simplicity is the lower accuracy of the model. For the test sequence the average prediction error is 0.12 for FMID (0.0497 before reduction) and 0.221 for ANFIS (0.053 before reduction). So the choice is to be made between linguistic relevance and modeling precision. The best fuzzy model, in terms of accuracy, was used for the prediction of the iron losses yielding the results presented in Table 2. There are also presented the result reported in [8] with neural network based models in order to be compared one with another.

Table 2 Iron losses evaluation using fuzzy magnetic model

	FeSi		FeNi	
	Max. relative error [%]	Conditions	Max. relative error [%]	Conditions
50 Hz	2,13	B_m=0,4 T	3,71	B_m=0,2 T
50 + 150 Hz	2,29	B_{m3}/B_m=0,15	4,33	B_{m3}/B_m=0,1
50 + 250 Hz	4,74	B_{m5}/B_m=0,1	4,86	B_{m5}/B_m=0,1

Table 3 Iron losses evaluation using neural network based magnetic model

	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

5. CONCLUSIONS

Different fuzzy models with lumped dynamic have been tested in order to give the prediction of the iron losses for a nonsinusoidal waveform of induction in FeSi (grain) and FeNi alloys. It was emphasis that using the same NARX assumption of the system, the same training and test input-output sequences and also the same number and structure of repressors, both fuzzy and neural network based magnetic models are yielding accurate evaluations. There are no significant differences between them and the choice is to be done only depending on user's ability to work with one or another.

ACKNOWLEDGMENT

This work was financed and developed in the framework of the LEONARDO DA VINCI pilot project with the contract number: RO/98/83550/PI.

REFERENCES

[1] EU Brite-Euram, "Characterisation of losses in electrical steels (CHARLES)", Project Rep. No. BRPR950019, 1998
[2] F. Fiorillo, A. Novikov, "Power losses under sinusoidal, trapezoidal and distorted induction waveform", *IEEE Trans. Magn*. vol. 26, pp. 2559-2561, 1990,
[3] F. Preisach, "Uber die Magnetishe Nachwirkung ", *Zeitschrift fur physic*, vol. 94, pp. 227-236, 1935
[4] I. Mayergoyz, "Mathematical models of hysteresis". *Springler*, New York, 1991.
[5] M. Saito, M. Namiki, S. Hayano, N. Tsuya, "Experimental verification of a Chua type magnetization model". *IEEE Trans. Magn.*, vol. 25, pp. 1876-1879, 1989.
[6] G.A. Maugin, M. Sabir, P. Chambon, "Coupled magneto mechanical hysteresis effects: application to nondestructive testing", in *Proc. of IUTAM*, pp. 255-258, 1987.
[7] A. Salvini, F.R. Fulginei, "Genetic algorithms and neural networks generalizing the Jiles-Atherton model of static hysteresis for dynamic loops", *IEEE Trans. Magn.*, vol. 38, pp. 873-876, 2002
[8] M. Temneanu, T. Balan, D. Balan, O. Postolache , "Iron losses prediction using neural network based magnetic model", *IMEKO TC4 Symposium*, Lisabona, pp.374-377, 2001
[9] J.J. Espinosa, J. Vandewalle, "Fuzzy modelling and identification, a guide for the user" SISCTA, Singapore, pp.279-286, 1997
[10] R. Babuska, "Fuzzy modelling and identification", *PhD Thesis*, Technical University of Delft, 1996.

Authors:

Marinel Temneanu, Lecturer PhD, Electrical Measurements Dept., Faculty of Electrical Engineering, Bdul Mangeron, 53, Iasi, Romania, Phone: 4032278683/1240, Fax: 4032237627, E-mail: mtemnean@ee.tuiasi.ro

Traian Balan, Professor PhD, Electrical Measurements Dept., Faculty of Electrical Engineering, Bdul Mangeron, 53, Iasi, Romania, Phone: 4032278683/1135, Fax: 4032237627, E-mail: tbalan@ee.tuiasi.ro

Dana Balan, Assoc. Professor PhD, Electrical Fundamentals Dept., Faculty of Electrical Engineering, Bdul Mangeron, 53, Iasi, Romania, Phone: 4032278683/1135, Fax: 4032237627, E-mail: dbalan@ee.tuiasi.ro

Cristina Temneanu, PhD Student, Electrical Fundamentals Dept., Faculty of Electrical Engineering, Bdul Mangeron, 53, Iasi, Romania, Phone: 4032278683/1241, Fax: 4032237627, E-mail: ctemneanu@yahoo.com