MODELLING OF INITIAL MAGNETIC CURVES OF NON-ORIENTED LAMINATED STEELS USING ARTIFICIAL NEURAL NETWORKS

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The article discusses modelling of the initial static magnetic curve of non-oriented laminated steels using artificial neural networks (ANN) for usage in electrical machine calculations. ANN enables modelling of nonlinear characteristics, which is crucial for developing electrical machines that meet application requirements. The initial magnetic curve must satisfy certain boundary conditions to be suitable for utilization in electromagnetic calculations. It is important to consider the measurement uncertainty in calculations that can be in case of ANN achieved by introducing noise injection. In conclusion, the significance and effectiveness of ANN in improving calculations and simulations in the field of electrical engineering are emphasized. This opens new possibilities for developing and understanding the magnetic properties of materials, emphasizing the significant impact and effectiveness of ANN in improving calculations and simulations.

Keywords:
artificial neural network,
initial magnetisation curve,
curve fitting,
oise inclusion,
non-oriented laminated steel

I Introduction

For the calculations of electrical machines, we require a model of the initial static magnetic curve of the non-oriented laminated steel, further on addressed as "iron". Accuracy, repeatability, and stability of the initial magnetic curve model is a key in the electromagnetic calculations. Even a slight deviation of the magnetic curve model can affect harmonic analysis, which in practice means a modified impact on the higher harmonics.

There already exist various analytical models that successfully describe the initial magnetic curve: Jiles-Atherton, Preisach, Dunhem, Coleman–Hodgdon, Stoner-Wohlfarth, Tellinen etc. [1]. Disadvantages vary from model to model, and they are most often associated with:

- complexity (solving differential equations etc.),
- oversimplification (assumes idealized conditions),
- large number of parameters,
- parameter sensitivity (small variation can significantly impact the model),
- calibration challenges,
- limited applicability (only for certain types of materials),
- fitting problems,
- lack of experimental validation.

The magnetic curve is typically highly nonlinear, making the ANN very suitable and powerful tool for modelling and prediction in various domains. In general, ANN can be used to model any nonlinear characteristic, however there are some challenges and limitations that need to be considered. The challenges of modelling using ANN include large amount of data for effective network training, computational resources, tuning of parameters to find the optimal combination of the hyperparameters, focus on learning patterns and data correlations rather than understanding causal data dependencies, and the potential occurrence of the model overfitting. All these are common problems in modelling using ANN. Overfitting occurs when the model becomes too complex and fits the trained data too closely, resulting in a poor generalization. There exist various of commonly used methods to prevent overfitting e.g., early stopping, regularisation, dropout etc. [2]. On the other hand, there are methods aiming to control the model's complexity by introduction of the randomness, i.e., the inclusion of noise improves generalization by introducing random data. The type of noise may vary, depending on the specific needs, such as Gaussian noise, random rotations, translations, scaling, flipping etc. This increases model robustness, improves generalization, and controls model complexity through regularization. It should be applied with caution; to avoid negative effect on the model's performance [3-6].

II Technical Information

A. Method description

We developed a model that will accurately approximate the response of the magnetic field density – B [T] in the iron in response to excitation with magnetic field strength – H [A/m], when using a limited number of experimentally obtained data points. To fabricate the model of the initial magnetic curve, which will be useful in further calculations, this must fulfil several initial requirements. Model must be a continuous function, continuously differentiable, strictly monotonically increasing, link the coordinate origin and must have μ_r=1 for high magnetic field strengths.

There were measured 12 data of SIWATT M800-50A non-oriented laminated steel. Data were obtained from the developer of the asynchronous motor calculation software [7]. Points are ranging from 1 T to 2 T. Data are shown in Table I. We used B as the input data and H as the output data.

Table 1: Experimental data

Data No.	1	2	3	4	5	6
H [A/m]	160	200	250	400	650	1000
B [T]	1,0097	1,1872	1,2889	1,4365	1,5315	1,60
Data No.	7	8	9	10	11	12
H [A/m]	1600	2500	5000	104	2·104	3·104
B [T]	1,6620	1,7254	1,8368	1,9563	2,0688	2,1051

B. Modelling procedure

Diagram in Figure 1 shows a two-step experimental process. In the first step a basic approximation of the two models in the range of the measured data was performed. Based on the results, the more appropriate one was selected. In the second step, the extended approximation – i.e., retraining was conducted. The selected baseline model was approximated to link the coordinate origin and the saturation point.

In both steps we used feedforward ANN. The Levenberg–Marquardt algorithm (LMA) was taking into account and all of the data used for training. A model with 2 hidden layers consisting of 2 neurons in the first layer and 3 neurons in the second layer was selected in both cases. Based on the preliminary tests we found this setup to be optimal for all the models.

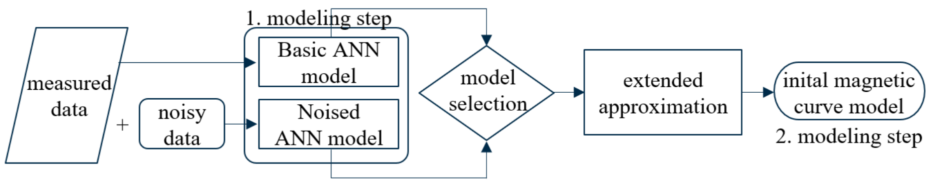

Figure1: Initial magnetic curve modelling process

In the first step, two approaches were analysed. The first approach, the *Basic ANN model*, utilized conventional ANN modeling methods without any additional techniques implemented. The second approach, the *Noisy ANN model*, incorporated a noise inclusion method: the Gaussian noise was introduced into the magnetic field strength data. The measured values were set as the mean values, with the assumed variance equal to 0,1 A^2/m^2. It was anticipated that this range effectively describes the scatter of the measurements and doesn't negatively affect the model's performance. Validation of the Gaussian noise was performed using comparative analysis between the models with/without the noise. Gaussian noise data were generated using *randn()* function in MATLAB software where 99 additional data sets were generated. A new matrix – *HM* (1) was created that included newly generated noisy data along with the measured data, where *v* represents the data variance, *N* the number of generated noisy data and *H* the magnetic field strength.

$$HM = v \cdot randn(N) + H \tag{1}$$

The suitable model was selected based on meeting the initial requirements. In the second modelling step only the selected model was analysed. To achieve a higher level of approximation accuracy, the subsequently added points were considered. These points were selected based on the initial requirements and preliminary research. The points were added to extend the initial model and cover the entire region of interest.

C. Model evaluation

Results are presented in Figure 2a. The curve of the *Noised model* appears smoother in comparison to the *Basic ANN model*, which exhibits larger transition area at higher excitation. This discrepancy is a result of the overfitting: when fitting the model, a smaller number of neurons mean that the model does not converge, while a model with one additional neuron leads to overfitting. Based on these results together with initial requirements, the *Noised ANN model* was selected as the basis for the second step of modeling.

The outcome of the second modelling step is the initial magnetic curve model, as depicted in Figure 2b. The model fully meets the requirements of being a continuous function, continuously differentiable and strictly monotonically increasing. The requirements of linking the coordinate origin and having μ_r=1 for the large excitation are met with only minor deviations. The error of the model when intersecting the coordinate origin amounts to $H(B=0\ \mathrm{T})=2{,}14\cdot10^{-2}$ A/m and the relative permeability at high excitation μ_r (B=2,3 T) =1,04. Based on the evaluation, it is determined that the magnitude of these errors should not significantly impact subsequent calculations and usfulness of the model.

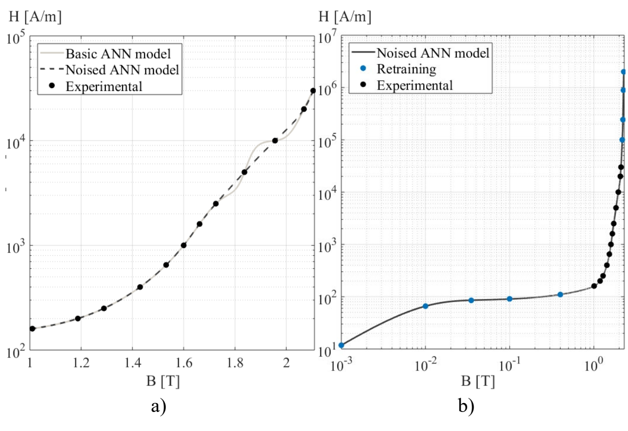

Figure 2: a) 1. modelling step - basic and Noised model, b) 2. modelling step - initial magnetic curve model

D. Conclusion

The advantages of modelling the initial magnetic curve using ANN are related to a higher model accuracy, simpler modelling process without the need to explicitly solve polynomial fitting, and possibility of exchanging with other programming languages. Such modelling method also enables the simultaneous modelling of multiple characteristics by using one ANN approximation network. However, when dealing with small data sets, insurmountable problems may arise in modelling with ANN, that cannot be solved by classical approaches. By introducing noise inclusion, it is possible to expand the data set accordingly, which increases the stability and accuracy of the model. Therefore, we conclude that the noise inclusion technique is a highly suitable tool for modeling the initial magnetic curve. Further investigations will be conducted to examine the effect of the initial magnetic curve model in the electrical machine calculations.

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