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Use of meta-modelling for identification and interpolation of parametric hysteresis models applied to the characterization of carbon steels

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Abstract

The meta-modelling approach based on an adaptive sparse grid interpolator has been studied for tackling the identification problem of parametric hysteresis models for steels with different microstructures. Two parametric models have been considered for the construction of the meta-model: the Jiles-Atherton model and the Mel'gui relation. The main advantage of the present approach is the separation of the calculation procedure in a computationally demanding off-line phase, which has to be carried out only once, and a very fast on-line evaluation. This decomposition is particularly interesting when a large amount of successive evaluations has to be carried out. Especially in the case that we are interested in a particular family of ferromagnetic materials (e.g. steels subjected to different treatments), where the sought parameters are lying in a specific interval, a single meta-model may be sufficient to be used for the study of a wide range of specimens. The steel samples considered in this study have been obtained from industrially produced low carbon steel, 84% cold rolled, and isothermally annealed in laboratory.

Keywords: hysteresis, parametric models, meta-modelling, identification, steel microstructure, thermal treatment

1. Introduction

The application of parametric hysteresis models like the Jiles-Atherton model [1] or the Mel'gui model [2], among others, is preceded by the so-called identification phase, where the input parameters of the model have to be determined based on a set of experimentally obtained curves. The most commonly used experimental sets for the model identification are the first order reversal curves (which are best-suited for the Preisach model) or symmetric minor loops with the reversal points lying on the first magnetization curve.

The usual practice for identifying the model parameters is to carry out an iterative optimization procedure, where the best fit between the theoretical curves and the measured ones is obtained via minimization of an ad-hoc discrepancy metric. Yet, in addition to the simple estimation of the parameters values, it is often desirable to assess the sensitivity or impact of these to the B(H) curve, and to compare different models in terms of correlation with other physical characteristics of the material, which stacks another iterative task on top of the identification procedure.

Such calculations imply intensive use of models and can rapidly prove cumbersome. The solution proposed in this paper consists to replace the hysteresis model by a meta-model, exploiting a database of simulation results. According to this approach, the original problem is separated into an off-line phase, linked with the construction of the

representative database, and an on-line one, where the output is derived from the stored data by means of an efficient interpolator. The advantages of this approach are the almost real-time evaluation, enabling the use of global optimization techniques and of statistical tools for confidence intervals estimation, sensitivity analysis and correlation calculations.

The aforementioned separation concept is particularly well suited in situations where one is interested in the study of a specific family of materials, given that the sought parameters are lying in a specific interval. This is the case of the present work, where the meta-modelling approach has been applied for the characterization of steels with different microstructures. Steel samples from industrially produced low carbon steel, 84% cold rolled, and isothermally annealed at low temperature (400°) in laboratory [3, 4] have been considered. The microstructural difference between these samples is the dislocation density, high in the heavily cold rolled sample, and lower in the annealed sample after recovery processes, have taken place.

The parametric models that are considered are the Jiles-Atherton model and the Mel'gui relation. The off-line construction of the meta-model is based on adaptive sparse grid algorithm [5]. The identification problem will be solved for two distinct steel samples of the above mentioned class and the results will be compared with the experimental curves.

2. The meta-modelling approach

2.1. Describing the hysteresis operator as an interpolator

In the context of this work we shall restrict ourselves to the scalar case, i.e. we shall assume that the magnetic behaviour of the material is isotropic. For such materials, the magnetic constitutive relation can be written as follows

$$M = M(H, H_0, H_{-1}, \dots) \quad (1)$$

where H is the applied magnetic field at time t , and H_{-i} , $i = 0, 1, \dots$ stand for the field reversal points (i.e. the points where the time derivative of H changes sign) at previous instances $t_{-i} < t$. For symmetric loops, however, only H_0 is needed to provide a unique description of the branch¹.

We seek to establish the following non-linear mapping $(H, H_0) \rightarrow M$ from the input space (H, H_0) to the magnetization values. There is a number of parametric models in the literature that has been proposed for the calculation of M like the Preisach model [6], the Jiles-Atherton model [1], the energetic model [7], the chemical model [8], the Mel'gui relation [2], just to cite some of them. Their common point is that they realize the above mapping based on an operational relation (they usually provide a differential equation for the magnetization) controlled by a set of parameters \mathbf{x} , which are model dependent and they are characteristic of the material. We can thus write formally

$$M = \mathcal{M}(H, H_0, \mathbf{x}) : H, H_0, \mathbf{x} \rightarrow M. \quad (2)$$

\mathcal{M} being a non-linear operator.

The main idea of the meta-model is to replace the above relation with an approximation of the direct model operator \mathcal{M} , which is now defined in the input parametric space \mathbf{x} and performs the **linear** mapping

$$M(H, H_0) = \hat{\mathcal{M}}_{H, H_0}(\mathbf{x}) : \mathbf{x} \rightarrow M(H, H_0) \quad (3)$$

where $\hat{\mathcal{M}}_{H, H_0}$ is the approximation of the original operator for a **given trajectory** in the (H, H_0) space.

The formal notation of (2),(3) reveals the key idea of the meta-model formalism. The operational relation of the original model is replaced by a linear functional, and hence evaluations using (3) can be computationally very efficient (in fact the computations reduce to mere interpolations). The calculations are thus decomposed in two steps: the creation of the approximation functional (also called as off-line phase), which is the computationally intensive step yet has to be carried out only once, and the evaluation (on-line phase), which is in general very cheap. This indirect calculation procedure via the use of the meta-model can be very interesting in cases where a large budget

¹It should be noticed here that hysteresis models with local memory can take into account only the last reversal point regardless the form of the excitation, which also complies the Madelung's rules. The Preisach's model, on the contrary, has non-local memory and hence an infinite number of reversal points has to be considered.

of successive calls to the model is required, as for example during optimization or for the calculation of statistical indices.

There is a number of different methods for the construction of the meta-model. The one examined in this work is based on the sparse grid approach, which will be presented in more detail in the following paragraph.

2.2. Hierarchical adaptive sparse grid methods

The use of sparse grid as numerical approach for the construction of the meta-model is motivated by the fact that it allows to overcome the curse of dimensionality which typically plagues the classical full-grid discretization schema once the parameter space overcome the four dimensions. The sparse grid method is based on the Smolyak algorithm [9] that allows to built a suitable interpolation function employing a minimum number of collocation points over a multi-dimensional space. The main idea of Smolyak algorithm is that only some elements produced by tensor product rules are important for properly representing the ground truth function. The set of points are known a-priori and are arranged on a level-wise grid.

In this work, we employ a hierarchical Adaptive Sparse Grid (ASG) aiming at improving the computational burden through a parsimonious selection of the SG points to be simulated. In the following, for sake of brevity and simplicity, we will present the ASG algorithm for an univariate scalar function. The extension to the multivariate functional case is quite straightforward. More details on this extension can be found in [10, 5].

Let us suppose to deal with a costly-to-evaluate function $f(\mathbf{x}) \in \mathbb{C}$ of a vector variable $\mathbf{x} \in \Omega \mid \Omega \in \mathbb{R}^{1 \times N}$ for which we want to find a suitable cheap-to-evaluate sparse grid interpolation $\hat{f}(\mathbf{x}) : \hat{f}(\mathbf{x}) \approx f(\mathbf{x}), \forall \mathbf{x} \in \Omega$. Thus, we define the hierarchical structure of basis function employed starting from the lower level ($l = 1$) up to the highest level $l = D$ for a univariate problem (i.e., $N = 1$). The hierarchical structure is defined through a set level-wise basis functions $\psi_l^{(i)}(x)$ with $x \in [0, 1]$. For each basis function is associated a supported node(s) $x_l^{(i)}$, which is defined through a recursive nested algorithm. The evaluation of the basis function onto the collocation node leads to $\psi_l^{(i)}(x_l^{(i)}) = \delta_{ij}$ where δ_{ij} being the Kronecker delta. In this paper we will employ a Newton-Cotes grid (sometimes known as Clanshow-Curtis) with equidistant nodes and linear basis function [10, 5]. The one-dimensional set of collocation points and the associated linear basis is given for the first three levels in Fig. 1a. Starting from the level 3 basis functions are all of the same kind, whereas level 1 and level 2 basis behaves of special kind. The sparse grid interpolant at the depth d is defined as

$$\hat{f}_d(x) = \hat{f}_{d-1}(x) + \sum_{i=1}^{n_d} \psi_d^{(i)}(x) v_d^{(i)}, \quad (4)$$

where n_d represents the number of basis function at level d , $v_d^{(i)}$ is the so-called hierarchical surplus for the i -th node

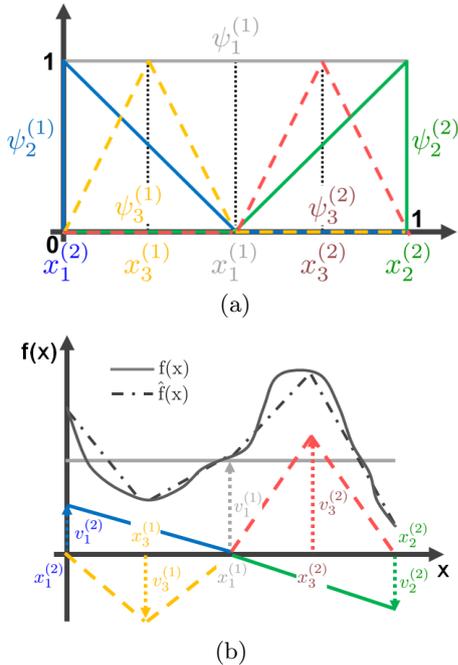


Figure 1: (a) Hierarchical basis function $\psi_l^{(i)}(x^{(i)})$ with the associated support nodes $x_l^{(i)}$ until $l = 3$. (b) One dimensional toy-function approximation by means of the above basis.

and it is defined as $v_d^{(i)} = [f(x_d^{(i)}) - \hat{f}_{d-1}(x_d^{(i)})]$. Looking at equation (4), we notice that the hierarchical surplus “weights” the contribution of the i -th basis $\psi_d^{(i)}(x)$ function on the interpolation process. This process is schematically shown in Fig. 1b.

Considering the definition of hierarchical surpluses, we can observe that they embed the information on the variation of the accuracy of the interpolation between two adjacent sparse grid levels. This information can be seen as a measure of the interpolation accuracy. In this framework, it can be exploited in order to adaptively refine the hierarchical sparse grid and therefore obtain an even more “sparse” set of samples. That is, when the underlying function behaves “smooth enough” on a sub region of the domain Ω , then the time consuming evaluation of the function is avoided. We can quantitatively define a kind of measure of the degree of smoothness by defining a suitable error and a tolerance associated to it. We define the estimation of the interpolation error as

$$\varepsilon_d(x) = \left\| \hat{f}(x) - f(x) \right\|_2,$$

where $\|\cdot\|_2$ stands for the L_2 -norm. Therefore, by comparing the above equation with the definition of hierarchical surplus, we have that the error at the depth $d - 1$ i.e., $\varepsilon_{d-1}(x)$, is equal to magnitude of the surplus $v_d^{(i)}$, thus it can be considered as local estimation of the error at the depth d . This adaptive refinement strategy, has been applied with success on electromagnetic problems, where accurate databases and metamodels with many parameters

have been generated and tested.

3. Acquisition of the experimental curves

3.1. Sample description

Samples from extra low carbon steel, with composition 0.03%C-0.19%Mn-0.13%Al-0.0035%N-0.012%P-0.01%Si, that had been industrially produced and cold rolled to a final thickness of 0.3 mm through a reduction of 84% were used in this study. A sample in the cold rolled state and a sample after having been isothermally annealed in the laboratory for 1000 s at 400° C have been used. The microstructure of the steel sample only experiences recovery processes at this low temperature, and hence, the only microstructural feature changing between these samples is the dislocation density and their configurations [3, 4].

3.2. Experimental B-H hysteresis loops

Major and minor magnetic B-H hysteresis loop determination was made using a single sheet tester system available at CEIT [11]. This is a completely digital, configurable and computer-aided system for measurements of magnetic hysteresis loops in a wide range of excitation frequencies for the purpose of material properties characterization. Major and minor hysteresis loops were recorded at 0.1 Hz using an encircling coil wound around the samples for each steel sample varying the maximum amplitude of the intensity of the magnetic field applied from around 200 A/m to 20 000 A/m in 10 steps.

4. Identification

The proposed meta-modelling approach has been applied for the identification of the Jiles-Atherton model and the Mel’gui relation for two steel samples subjected to different treatments: a cold rolled sample and a thermally annealed sample.

A single meta-model has been built for each parametric model and the experimental curves have been identified by minimizing the following cost function

$$f(M_{meta}, M_{exp}) = \frac{\int_H |M_{meta}(H) - M_{exp}(H)| dH}{\int_H |M_{exp}(H)| dH} \quad (5)$$

where $M_{exp}(H)$ are the experimental data as function of the applied field (for both external descending and ascending branches) and standing for the element of the meta-model $M_{meta}(H)$. The numerical values for the models parameters obtained via the optimization are given in Table 1 and Table 2. The curves that correspond to these parameters are compared with the experimental ones in Fig. 2. It can be observed that the Jiles-Atherton model fits better to the general shape of the curve, while the Mel-gui model provides a worse fitting in the knee region of the loops.

Spec.	M_s	α	a	k	c
CR	$1.428 \cdot 10^6$	$0.924 \cdot 10^{-3}$	600	650	0
TA	$1.5 \cdot 10^6$	$1.169 \cdot 10^{-3}$	600	500	$9.429 \cdot 10^{-6}$

Table 1: Identified parameters of the Jiles-Atherton model for the cold rolled (CR) and the thermally annealed (TA) specimens.

Spec.	M_s	H_c	M_r	M_c	χ_{in}
CR	$1.428 \cdot 10^6$	700	$0.815 \cdot 10^6$	$0.272 \cdot 10^6$	33
TA	$1.41 \cdot 10^6$	450	$1.051 \cdot 10^6$	$0.351 \cdot 10^6$	84

Table 2: Identified parameters of the Mel'gui model for the cold rolled (CR) and the thermally annealed (TA) specimens.

The thermally annealed sample after having experienced the recovery processes shows a much lower coercive field value H_c [3, 4] and higher remanent magnetization, M_r , [12]. These two experimental parameters are reflected in H_c and M_r parameters of the Melgui model, as well as in the pinning parameter k of the Jiles-Atherton model, which is a measure of the width of the hysteresis loop and is proportional therefore to the coercive field H_c [13].

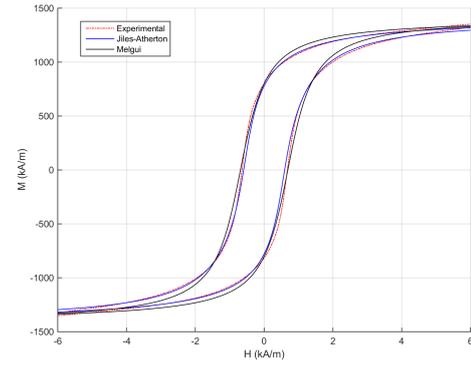
Conclusions

The meta-modelling approach has been applied for the identification of the hysteresis curves for steels that have undergone different treatments. Two meta-models, based on the Jiles-Atherton parametric model and the Mel'gui relation, have been constructed and used for the identification of both steel samples.

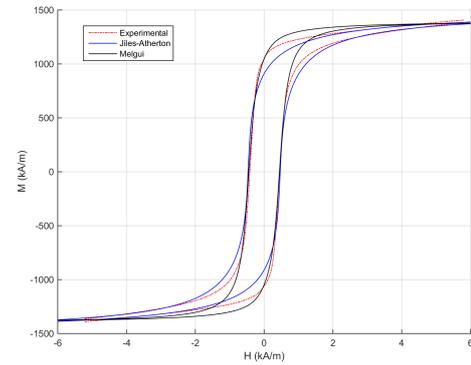
Identification, parametric studies and calculation of statistical indices can be performed by using a properly pre-calculated meta-model for entire families of materials. Future work will concentrate on the use of meta-models for studying the influence of different microstructural parameters in the hysteresis characteristics.

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(a)



(b)

Figure 2: Comparison of the theoretical curves obtained by two meta-models constructed after the Jiles-Atherton model and the Mel'gui relation with the experimental curves for (a) the cold rolled sample and (b) the thermally annealed sample.

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