AN OPTIMISATION OF EXPERIMENTAL DATA PROCESSING FOR MAT METHOD APPLICATION

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Summary Magnetic adaptive testing (MAT) is a new method of magnetic non-destructive inspection of structural mechanical properties of magnetic construction materials. Principle of MAT consists in analysis of several magnetic properties I a wide range of input variables and to find the degeneration function with optimum correlation to inspected degeneration physical process. This involves processing of large amounts of experimental data. We present a new software tool for data processing based on application of various digital filters. A novel approach of statistical analysis and thresholding using masks was introduced to data analysis and thus qualitatively improving MAT optimisation process.

1. INTRODUCTION

During lifetime of any industrially used construction materials, they undergo mechanical or thermal stresses and overloading, service-based or accidental. This results in modification of material structure and thus in degeneration of mechanical properties. It is crucial to detect the material deterioration early before end of its service lifetime. Magnetic non-destructive diagnostic methods are based on sensitive coupling of the magnetization process to the structural/stress variation of material and can serves as possible indication of damage parameter. Magnetic adaptive testing (MAT) has been developed for the purpose of optimisation of magnetic non-destructive testing [1]. Classical magnetic diagnostic methods investigate magnetic response to material degeneration by measuring major hysteresis loop and corresponding magnetic parameters (remanence, coercivity) [2]. MAT investigates family of symmetrical minor hysteresis loops to obtain optimum minor loop with optimum diagnostic properties, i.e. most sensitive to material structural/stress variations and stable to fluctuation of measuring conditions. Thus we get the dependence of "degeneration" adapted to given material and given structural/stress variation.

In typical MAT application, the sequence of reference samples with different degree of degeneration (toroids in most cases), are specially magnetized. The intensity of applied magnetic field has triangular shaped waveform, with amplitude increasing a defined constant step in each period, up to defined maximum, and maintaining constant dH/dt. Under these conditions, induced voltage in pick-up coil is proportional to differential permeability [3]. Data of differential permeability are then arranged into datasets or matrices, each corresponding to one reference sample and all available *degeneration functions* – as a feature of some physical process with a link to material degeneration δ – are computed. The degeneration function is generally function of all MAT input parameters p_i, see Equation (1)

$$D = f(\delta, p_1, \ldots\ldots, p_n) \qquad (1)$$

Similarly to Preisach model of ferromagnetic hysteresis [4], instantaneous values of applied magnetic field $h_a = h_a(0, \ldots, N)$ and magnetic field amplitudes $h_b = h_b(0, \ldots, M)$, in each period of step by step increasing triangular magnetic field, are chosen as the MAT input parameters. N is usually the number of applied magnetic field samples (sampling points) on descending part of minor hysteresis loop [4] and M is the number of constant steps in amplitude of applied magnetic field *i.e.* number of minor loops. Then in this case the degeneration function is the dependence of differential permeability on two input parameters/variables

$$D = \mu_{diff}(\delta, h_a, h_b) \qquad (2)$$

For each step of degeneration parameter δ the data of differential permeability are smoothed and interpolated to (h_a, h_b) datasets – matrices. The datasets are then normalized by the reference dataset, in general the matrix of data for δ=0. Corresponding matrix elements across the sequence of reference samples with different δ form the degeneration functions. An optimum degeneration function corresponds to optimal measuring conditions – input magnetic parameters h_a, h_b. This function is then used as the calibration curve for non-destructive inspection of unknown samples of the same material and type of degeneration.

One of the damage mechanisms is a ductile damage, which corresponds to defects (creation and development of micro-cracks or micro-cavities) induced by large plastic deformation [5]. In this paper, we test a new approach to optimisation of experimental data (differential permeability) processing for plastic part of the strain tensor ε_{p11} as the degeneration parameter. The aim of this paper is to present the newly developed software tool and algorithms, that would integrate functions required for MAT data processing, evaluation and add the possibility of automatic data analysis.

2. EXPERIMENTAL

As an experimental data for the optimisation process of analysis we used the data of differential permeability of low-carbon steel (behanite) and their change with plastic deformation. This material was chosen as a model material for this investigation because of its well-known dependence of dislocation density on the plastic strain. Four cylindrical rods with initial diameter 14 mm were differently plastically deformed with the constant strain rate 3.33×10^{-4} s^{-1}. The loading diagrams of the prepared rod samples are shown in Fig. 1. The values of the tensile strain ε (plastic part of strain tensor), after unloading, were 2.2, 5.4, 10.2 and 15.2%, respectively.

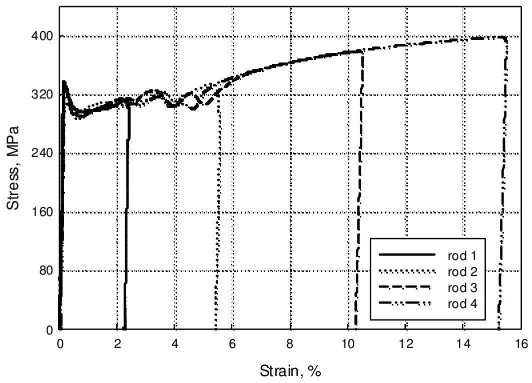

Fig. 1. Loading diagram of behanite samples.

For the magnetic measurements 3 mm thick discs were cut from the rods (perpendicularly to the strain direction) and a hole was drilled in the middle of each disc, so that the prepared samples were closed rings (toroids) with cross-section of about 5 mm^2. Water-beam cutting was used for "gentle" mechanical processing of the sample, to avoid additional undesirable internal mechanical stresses. An outer magnetizing coil with 50 turns was wound around whole perimeter of each ring and an inner pick-up coil with 100 turns. Thus, we obtained five sets of samples with different plastic deformation ε, the reference set was with ε=0 (non-deformed rod). The set of quasi-static differential loops or minor hysteresis loops was measured by experimental set-up, discussed in our previous paper [3]. Fig. 2 shows a set of differential relative permeability loops for the sample with ε=0, where h_a changes with a constant step of 50 A/m up to maximum magnetic field intensity of 1 kA/m. For the comparison a set of minor hysteresis loops corresponding to the same magnetisation process can be seen in Fig. 3. Note that the accuracy of the loops at higher fields is affected by very high dynamic range required due to sharp peaks in the induced voltages even at very smooth changes of exciting field.

3. DATA PROCESSING - OPTIMISATION

Magnetic adaptive scheme has been successfully applied on several material samples [6, 7]. Software tools used for data processing solved partial problem only: the arrangement of data into datasets, data smoothing and data interpolation. Further analysis has been done manually using general-purpose scientific graphing software tools. No specialized software providing data analysis has been used so far.

In our approach a more examiner-choice oriented approach is required. This leads to an idea of bringing more statistical approach and fuzzy logic methods. The data can be analysed against number of criteria, each criterion expressed as the *preference function*. The degeneration function is then selected at *places* of correlated high preference. To simplify the selection, the criterion functions can lead to *selection masks* that express the preference as true/false, based on satisfying the specified criterion. In other words, the selection mask is a matrix of true/false values, true for those degeneration functions, whose criterion is above specified threshold. Threshold selection can be automatic and by weight-balancing of selection criteria, the algorithm is able to select finite set of selected degeneration functions.

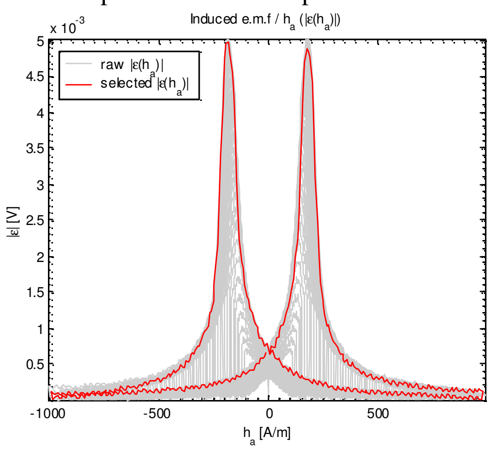

Fig. 2. Set of relative differential permeability μ_{diff} loops for ε=0.

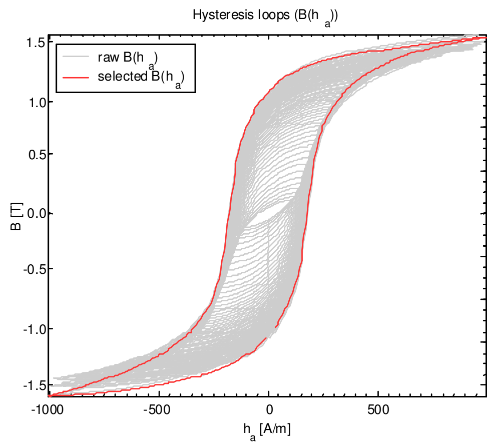

Fig. 3. Set of minor hysteresis loops for non-deformed steel sample.

The selected degeneration function should be:

- defined at points of highest sensitivity (high relative change)
- defined at points of high stability (low surface-curvature of $\mu_{diff}(h_a,h_b)$), deviation of measurement parameters from optimal should not lead to significant change in degeneration function
- should be linear to provide similar sensitivity in whole range of degeneration
- should be monotonous, to be able to find inverse function

MATLAB 6.1 computing environment was selected for the tool implementation. MATLAB represents an industry standard in technical computing, it offers a lot of high-level functions, and it includes data presentation methods and interfaces. Grid of uniformly spaced h_a-h_b values is computed first, using MATLAB *meshgrid* function. The sets of data scattered in h_a-h_b space are then interpolated using triangle-based cubic interpolation with built-in MATLAB *griddata* function. Several data processing procedures, or “filters” have been implemented to process interpolated datasets. The examiner is able to select filters that are sequentially applied on the datasets. Without significant reduction of the information in the data, low-pass filter can be applied to suppress unwanted distortion.

The filter was implemented as a convolution with impulse response of a LP filter. The median filter (commonly used in image processing) and custom filter are providing as a template for implementation of filters. The examples of application of interpolation and filtering on experimental data are shown in Figs. 4 and 5. The reference material sample usually represents “zero” degeneration factor, e.g. δ = ε = 0. Dataset corresponding to reference sample is then used to normalize all the datasets with respect to this reference one. Using *ratio-normalized* filter, all $\mu_{diff}(n,I)$ functions are divided sample-wise with $\mu_{ref}(n,I)$. The *difference-normalized* filter is available too, where $\mu_{ref}(n,I)$ is subtracted sample-wise from all $\mu_{diff}(n,I)$ functions. The *global mask* is obtained by logical multiplication of all of selection masks. This mask represents degeneration functions that fulfil all specified criteria. Examiner is able to select masks that will be applied to create the global mask, as well as fine tune criteria by means of specifying thresholds. Our software tool (*permeab*) enables to create a global mask from sensitivity mask, stability mask linearity mask and monotonicity mask. For example sensitivity mask for 65% threshold is shown in Fig. 6. The sensitivity is defined as the value of linear function gradient that approximates the degeneration function. In other words, linear

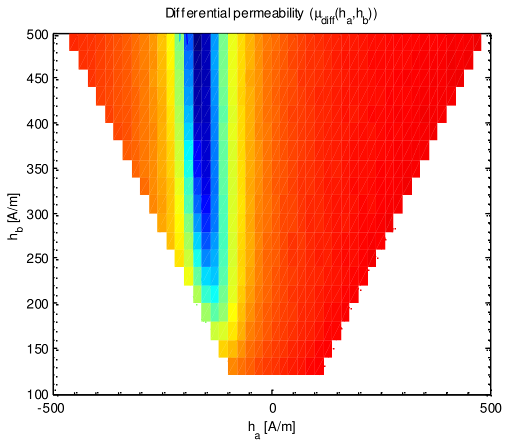

Fig. 4. The presentation of distribution function $\mu_{diff}(h_a, h_b)$ for ε=0 after interpolation.

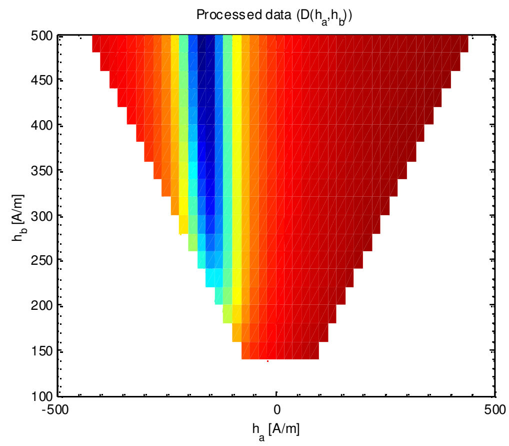

Fig. 5. The presentation of the same dataset as in Fig. 4 processed with LP filter.

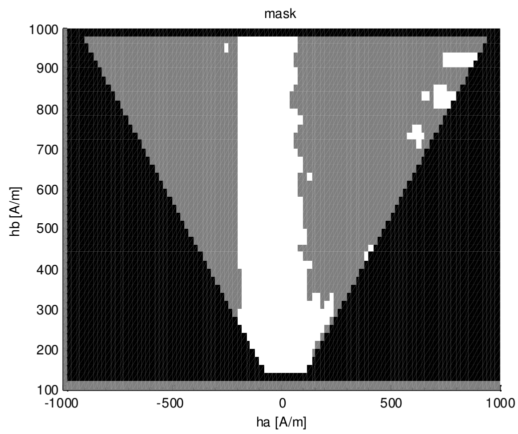

Fig. 6. Sensitivity mask for threshold of 65%.

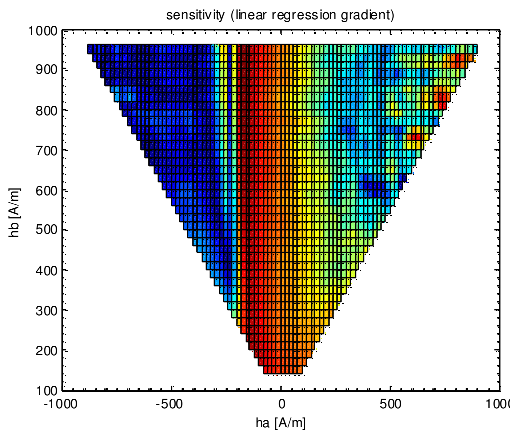

Fig. 7. Sensitivity preference function.

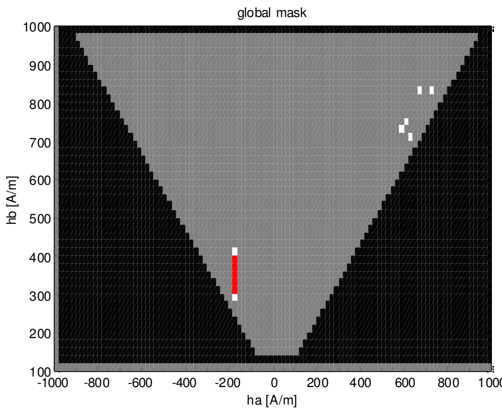

Fig. 8. Global optimization mask

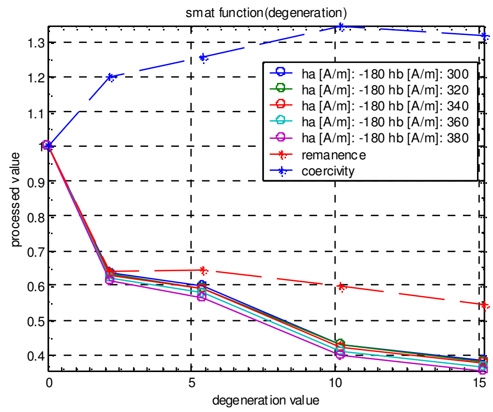

Fig. 9. Optimal MAT degeneration functions and classical magnetic parameters functions

approximating polynomial is computed for every degeneration function in form $y=ax+b$ and sensitivity preference function is surface of a-values on h_a, h_b plane (Fig. 7). Threshold specifies lower limit of sensitivity, as a fraction of maximum sensitivity of the whole dataset. The white areas designate (h_a, h_b) values that meet the criterion 65 % from maximum sensitivity. Global mask for differential permeability data, as a combination of all masks (sensitivity, stability, linearity and monotonicity) is presented in Fig. 8 and several corresponding degeneration functions from optimum "area" (designed by red colour) are shown in Fig. 9. For comparison the degeneration functions using traditional magnetic hysteresis data are presented too.

4. CONCLUSION

The software tool for application of MAT technique was implemented. The software unifies the functionality required for processing of MAT data, data analysis and data presentation. A novel approach of statistical analysis and thresholding using masks was introduced to data analysis. Despite lower level of automation implemented tool enables the examiner to compare the results quickly and conveniently by means of applying various filters, specifying various degeneration descriptors (e. g. using derivative or integral filters) and balancing selection masks, thus qualitatively improving MAT analysis. Further enhancement of existing solution by means of implementation of new processing filters or new selection masks is possible.

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