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FUZZY CHARACTERIZATION OF FLAWED METALLIC PLATES WITH EDDY CURRENT TESTS

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Abstract—Eddy Current Techniques (ECT) for Non-Destructive Testing and Evaluation (NDT/NDE) of conducting materials is one of the most application-oriented field of research within electromagnetism. In this work, a novel approach is proposed in order to characterize defects on metallic plates in terms of their depth and shape, starting from a set of experimental measurements. The problem is solved by means of a hybrid classification system based on Computation with Words (CWs) and Fuzzy Entropy (FE). They extract information about the specimen under test from the measurements. Main advantages of proposed approach are the introduction of CWs as well as the usage of the FE based minimization module, in order to improve flaw characterization by a low computational complexity system.

1. INTRODUCTION TO THE PROBLEM

Non Destructive Testing (NDT) plays a remarkable role within the framework of defect identification in metallic plates, with special regard to those sectors where the integrity of the material is strictly required. As a consequence, the detection of defects together with the relevant shape classification provides the operator useful information about the actual mechanical integrity of the specimen [1, 2]. Direct [3–5] and inverse problems [6, 7] exploiting eddy current tests are well known in scientific literature. At the state-of-the-art, the open problems involve in-depth location and shape determination of a defect starting from experimental measurements. Both of them are ill-posed inverse problems, because of differently shaped defects, located into the inspected material at an unspecified deepness, can rise to totally similar signals. The conventional approaches to classification, which assign a specific class for each defect, are often inadequate because each defect may embrace more than a single class. Fuzzy Set theory, which has been developed to deal with imprecise information, can provide a more appropriate solution to this problem. This paper aims to deal with the classification of defects, both Inner (ID) (the probe lies on the same side of the plate where the defect is located) and Outer (OD) ones (probe and defect are on opposite sides of the plate), in terms of their depth. An approach based on CWs has been introduced, so obtaining banks of "IF...THEN" fuzzy rules, in virtue of which the system under investigation behaves as a linguistic structure. In CWs, a word is viewed as a label of a granule, i.e., a fuzzy set of points drawn together by similarity, with the fuzzy set playing the role of a fuzzy constraint on a variable. The premises are expressed as propositions in a natural language. For computational purposes, the propositions are expressed as canonical forms. They serve to evidence the fuzzy constraints, which are implicit in the premises. The inference rules are exploited to propagate the constraints from premises to conclusions. In order to point out the goodness of the procedure, a comparison with traditional FISs with Sugeno's inferences-type has been taken into account. In addition, a novel approach is proposed by considering a sort of fuzzy clustering with a FE calculus to characterize the shape of analyzed defect. In particular, the fuzzy formulation of Shannon entropy is used to obtain mathematical and experimental models of a Fuzzy machine for pattern recognition, with optimal inference capabilities and minimal entropy values. In particular, to get the minimal number of rules describing the system behavior, we have implemented a suitable FIS with Minimal FE (MFE). This paper is organized as follows: after a Section 2 theoretically describing the exploited non-destructive and heuristic techniques, the collected experimental database is presented in Section 3. Then, the achieved best results are presented in Section 4. Finally, some conclusions are drawn.

2. A BRIEF THEORETICAL INTRODUCTION

Eddy current technique is a non-destructive methodology based on Foucault theory. It is caused by a moving magnetic field intersecting a conductor or vice-versa. The relative motion causes a circulating flow of electrons, or current, within the conductor. These circulating eddies of current create electromagnets with magnetic fields that oppose the change in the external magnetic field, according to the Lenz's law. The stronger the magnetic field, or greater the electrical conductivity of the conductor, the greater the currents developed and the greater the opposing force. An eddy current is a swirling current set up in a conductor in response to a changing magnetic field. By Lenz's law, the current swirls in such a way as to create a magnetic field opposing the change; to do this in a conductor, electrons swirl in a plane perpendicular to the magnetic field. Because of the tendency of eddy currents to oppose, eddy currents cause energy to be lost. More accurately, eddy currents transform more useful forms of energy, such as kinetic energy, into heat, which is generally much less useful [8, 9].

A practical application of eddy current phenomenon is just the identification of faults in mechanical integrity of metallic specimen. In this case, a presence of flaw, for instance, disturbs the normal distribution of current within the material, causing a brusque variation of the measured electromagnetic field. Within this framework, an AC electric current tends to flow at the *skin* of the conductor. The depth below the surface of the conductor at which the current density decays to $\frac{1}{e}$ of the current density at the surface (J_S), i.e., the so called *skin depth* d, is determinable as $d = \sqrt{\frac{2\rho}{\omega\mu}}$, where ρ is the resistivity of conductor, ω is the pulse of current and μ is the absolute magnetic permeability of conductor. It is the well known *skin effect*. Nowadays, characterize a defect starting from measured electromagnetic quantities is an open question, even because the problem is complicated by its ill-posedness. In fact, totally different defects can rise to similar eddy current signals. Therefore, it is necessary to regularize the inverse problems, for example by using heuristic techniques based on a "learning by sample" method. In the remaining body of this section, our proposed approach will be theoretically described.

2.1. The Fundamental Theory of CWs Approach

Computing is centered on manipulation of numbers and symbols. In contrast, Computation with Words (CWs) is a methodology in which the objects of computation are words and propositions drawn from a Natural Language (NL) [10, 11]. CWs is a necessity when the available information is so much imprecise to justify the use of number and when there is a tolerance for imprecision which can be exploited to achieve tractability, robustness, low solution cost and better rapport with reality. A basic generic problem in CWs consists of a collection of propositions, namely an Initial Data Set (IDS), expressed in a NL, which can be replied by using a namely Terminal Data Set (TDS) with the same language. The problem is to derive TDS from IDS. For this purpose, we translate the IDS propositions into their canonical forms, which collectively represent antecedent constraints. By using some rules for constraint propagation, antecedent constraints are reformulated into consequent constraints. Finally, consequent constraints are translated into a NL by means of linguistic

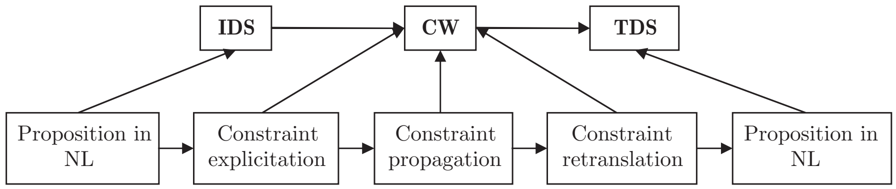


Figure 1. Conceptual structure of CWs.

approximation, yielding the terminal data set (Fig. 1). Therefore, two core issues: representation and propagation of fuzzy constraints. The former is based on the test score semantics: a proposition p in a NL can be expressed as a network of fuzzy constraints. In particular, they can be represented in the form X *isr* R. This expression is the canonical form of p, where X is the constrained variable, R is the constraining relation and *isr* is the so called variable copula, defining the relation between R and X. More specifically, the role of R in relation to X is defined by the value of the discrete variable r (Fig. 1). Once the propositions into the IDS are expressed in their canonical form, the groundwork is laid for fuzzy constraint propagation. The rules governing fuzzy constraints propagation (latter core in CWs) effectively are the rules of inference in FISs. In addition, it is helpful to have rules governing fuzzy constraint modification. In particular, *if X is m A X is f(A)* where m is a sort of linguistic modifier such as not, very, more or less, and *f(A)* defines the way in which m modifies A. For instance, *if m=not then f(A)=A' (complement)* and *if m=very then f(A)=2A (left square)*, where $\mu_{2A}(u) = (\mu_A(u))^2$. The principal rule governing constraint propagation is a generalized extension principle which in schematic form may be represented as:

$$\frac{f(X_1, X_2, ..., X_n)\ is\ A}{q(X_1, X_2, ..., X_n)\ is\ q(f^{-1}(A))} \tag{1}$$

In this expression, $X_1, X_2, ..., X_n$ are database variables; the term above the line represents the constraint induced by the IDS; and the term below the line is TDS expressed as a constraint on the query $q(X_1, X_2, ..., X_n)$. In the latter constraint, $f^{-1}(A)$ denotes the pre-image of the fuzzy relation A under mapping $f : U \rightarrow V$, where A is a fuzzy subset of V and U is the domain of $f(X_1, X_2, ..., X_n)$. Expressed in terms of the membership functions of A and $f^{-1}(A)$, the generalized extension principle reduces derivation of the TDS to the solution of the constrained maximization problem $\mu_q(X_1, X_2, ..., X_n)(\nu) = sup_u\,(\mu_A(f(u_1, u_2, ..., u_n)))$ in which $u_1, u_2, ..., u_n$ are constrained by $\nu = q(u_1, u_2, ..., u_n)$.

2.2. An Overview of FE Minimization

In a pattern classification problem, u_{jk} is the level of fuzzy membership of j-th defect to k-th class ($k \in \mathbb{N}; k = 1, 2, ..., N$). Let N classes are given, the shading-type partition produces N informative layers representing membership levels of the defects to the selected classes. Shannon index [12] has been widely applied to evaluate the fuzziness degree of a fuzzy classification. Entropy of a defect, H, i.e. its amount of statistic information, is $H = \sum_{k=1}^{N} u_{jk} ln(u_{jk})$ where $ln(u_{jk}) = 0$ when $u_{jk} = 0$ [13]. According to fuzzification of Shannon Entropy principle, a new FE-based approach has been considered for implementing a Minimal Fuzzy Entropy Decisional Model (MFEDM) for each considered feature. In order to build each MFEDM, the following algorithm has been considered:

(i) let $X = \{x_1, x_2, ..., x_n\}$ an universal set of pattern space elements;

(ii) let $\tilde{A}$ be a k-elements fuzzy set ($k < n$) defined on an interval of pattern space; membership degree mapping of x_i elements into the fuzzy set $\tilde{A}$ is denoted as $\mu_{\tilde{A}}(x_i)$;

(iii) let $C_1,\ C_2,\ ...,\ C_m$ be the m classes into which the n elements arc divided;

(iv) let $S_{C_j}(x_n)$ represent a set of elements of j-th class into the universal set X;

(v) let us define D_j as the match degree with the fuzzy set $\tilde{A}$ for elements of j-th class in an interval, where $j = 1, 2, ..., m$: $D_j = \dfrac{\sum_{x \in S_{C_j}(x_n)} \mu_{\tilde{A}}(x)}{\sum_{x \in X} \mu_{\tilde{A}}(x)}$;

(vi) let us define FE of elements of j-th class in an interval $FE_{C_j}(\tilde{A}) = -D_j \log_2(D_j)$;

(vii) let us define FE (non-probabilistic entropy) in an universal set X for elements in an interval $FE(\tilde{A}) = \sum_{j=1}^{m} FE_{C_j}(\tilde{A})$. Therefore, the term match degree for D_j has been coined.

In order to explain the applicative algorithm of previously proposed mathematical model, let us consider an l-dimensional pattern $p \in X,\ p = \{p_1, p_2, ..., p_l\}$ (train pattern), which is composed by l features (inputs) and belongs to class $C_j,\ 1 \leq j \leq m$. A Fuzzy System is obtained from a train patterns' set by subtractive clustering, with a user-defined number of fuzzy membership functions (FMFs) for each input (n_{fmf}). Considering the r-th input ($1 \leq r \leq l$) of each train pattern p_t, let us define a number of intervals equal to ($n_{fmf} + 1$): interval boundaries are defined as follows: left-most interval boundaries are $[min(p_t, r), c_1]$; boundaries of each s-th internal interval are

$[c_{s-1}, c_{s+1}]$; right-most interval boundaries are $[c_{n_{fmf}-1}, max(p_t, r)]$. For each s-th interval, $FE(\tilde{A}_s)$ is calculated according to the previously presented equations: thus FE of considered r-th input (FE_r) is the summation of all $FE(\tilde{A}_s)$, $s = 1, 2, ..., (n_{fmf} + 1)$. It is the total amount FE_{tot} of FE. When FE_{tot} has a minimum, the procedure is stopped and the relative FIS is returned. It is a particular FIS, having the lowest number of rules and Minimal FE (MFE), without loosing on generality and on informative content.

3. THE EXPERIMENTAL DATABASE

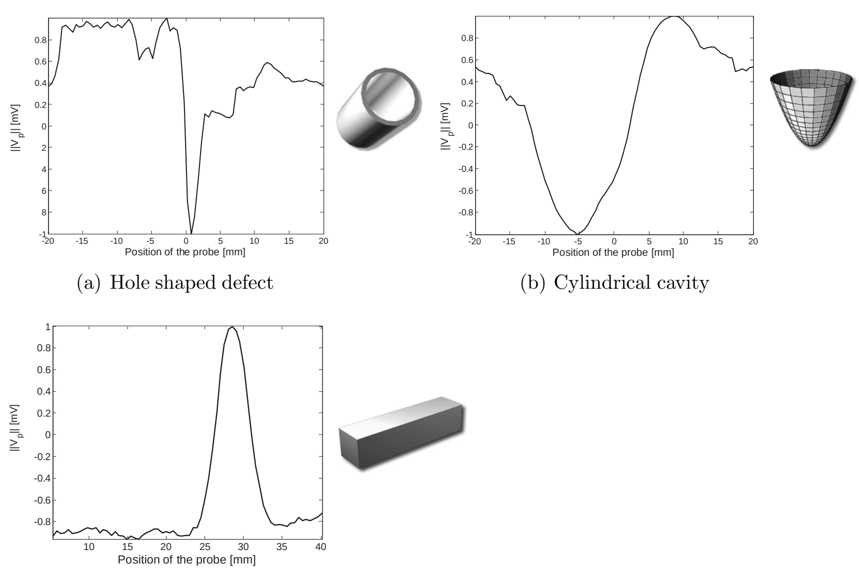
Experimental measurements have been carried out at Non Destructive Testing Lab, DIMET Department, Universitá "Mediterranea" of Reggio Calabria.

First of all, in order to characterize the existing flaws in terms of their shapes, hole shaped, cylindrical cavity shaped and rectangular shaped artificial defects have been considered on INCONEL600 specimens (140×140×1.25 mm). INCONEL600 is an alloy composed by 70% nichel, 15% chrome and 8% iron, having an excellent resistance to corrosion and high temperatures, with $\sigma = 10^5$, $\mu = \mu_0$). The applied sensor was a Fluxset©-type probe [14], longitudinally moved over the specimen by means of a 0.5 mm-step automatic scanning procedure. A driving signal - triangular shape, 125 kHz frequency, 2Vpp amplitude — was applied to saturate the core material inside the probe. External sinusoidal exciting currents of 292 mA rms (frequency 1 kHz), 503 mA rms (frequency 1023 Hz) and 170 mA rms (frequency 5 kHz) have been exploited for hole, cylindrical cavity and rectangular defects respectively. A set of 29 measurements has been carried out in order to retrieve a dataset useful for our experimentations. Different exciting settings of Fluxset© are very important in order to quantify the point-to-point trend of the magnitude of the pick-up voltage $\|V_p\|$. In this case, in fact, the skin depth phenomenon requires a balancing between exciting frequency and electric conductivity of used material, in order to reach significant examination depths. Consequently, both the exciting currents and frequencies were set in order to span the whole of depth of each specimen. Subsequently, the collected dataset has been used in order to train and test a suitable FIS with a MFE for defect's shape recognition. In order to train our FIS, a pre-processing action of feature extraction has been taken into account. In particular, both for magnitude and phase of V_p, the following statistical quantities (features) have been calculated: average, standard deviation, skewness and kurtosis. For each feature, it has been considered the ratio between the value computed on the area in which the defect takes place and

Table 1. Codify used to train the FIS for flaw characterization in terms of deepness.

Hole shaped defect	Cylindrical cavity	Crack
1	2	3

the value computed on the whole of signal (inputs of FIS procedure). Each pattern has been related to a modeling of flaw's shape and a sort of user-defined codify (outputs of FIS procedure) as shown in Fig. 2 and Table 1. Finally, the collected dataset has been split into a train (trainDB) and a test (testDB) databases: the former composed by 25 patterns, the latter composed by remaining patterns. Fig. 2 clearly depicts the ill-posedness of the problem for defect's shape characterization starting from experimental eddy current measures. In fact, let us denote how holes and cylindrical cavities shows similar trend of correspondent eddy current signal, in spite of the different geometric characterizations. Differences in magnitude of plotted $\|V_p\|$ are due to the exciting frequency and current.



(a) Hole shaped defect

(b) Cylindrical cavity

(c) Crack

Figure 2. Magnitude of $\|V_p\|$ and geometrical modeling for: a) an hole shaped defect; b) a cylindrical cavity shaped defect; c) a rectangular crack defect.

Subsequently, plates with rectangular cuts (0.2x5 mm), having depths of 20%, 40%, 60% and 100% of the plate thickness respectively, have been inspected in order to implement a CWs based system able to estimate the deepness of a flaw. Also in this case, 29 full scannings were run. The following quantities were selected (inputs of procedure): the peak-to-peak value of voltage's phase ($\angle(V)_{peak}$, [degree]); the exciting current i_{exc} ([mA]). Each input pattern has been linked to the corresponding flaw's depth by using a suitable class codification (output of procedure).

4. PERFORMANCES OF THE EXPLOITED MODELS

4.1. CWs for Deepness of Defects

As a first step in CWs procedure to identify defects on metallic plates, we need to introduce a concept of granule which, typically, is defined as a fuzzy set of points drawn together by similarity. In our application, the input set is represented by exciting current and the phase of the pick-up signal, whereas the output is the class of defect's depth (Fig. 3). A suitable granulation with a gaussian membership function has been chosen for each class. Starting from a bank of fuzzy rules, e.g., *if exciting current if large and phase is very small then class is small*, it is possible to represent fuzzy constraints using the Explanatory Database (ED) procedure (Fig. 1) in order to write fuzzy rules by CWs. The exciting current is a Parameter that defines the *Characteristic_exciting*. According to proposition "exciting current is large", ED is the following: *ED=Characteristic_exciting[Parameter; Field]+Large[Field; μ]*. Here *Characteristic_exciting* is a relation involving *Parameter* and *Field*, *Large* is a relation involving *Field* and the membership degree. Then the proposition $p_1 = X_1$ *is* R_1 = *"current is large"* becomes ${}_{Field}$*Characteristic_exciting[Parameter=current] is Large[Field; μ]*. Likewise, the proposition $p_2 = X_2$ *is* R_2 = *"phase is verysmall"* becomes ${}_{Field}$*Characteristic_exciting[Parameter=phase] is Verysmall[Field; μ]*. Output of the first rule is $q = X_0$ *is S= "class is small"*; ED is ${}_{Depth}$*Characteristic_defect[Parameter=class] is Small[Depth; μ]*. The final resulting rule is the following: ***If*** ${}_{Field}$*Characteristic_exciting[Parameter=current] is Large[Field; μ]* ***and*** ${}_{Field}$*Characteristic_exciting[Parameter=phase] is Verysmall[Field; μ]* ***then*** ${}_{Depth}$*Characteristic_defect[Parameter=class] is Small[Depth; μ]*.

We obtain a bank of modified rules applying a sort of manipulation of fuzzy constraints. For example, a typical rule can be written as: ***If*** ${}_{Field}$*Characteristic_exciting[Parameter=current] is Large[Field; μ]* ***and*** ${}_{Field}$*Characteristic_exciting[Parameter=phase] is Small[Field;* μ^2*]* ***then*** ${}_{Depth}$*Characteristic_defect[Parameter=class] is Small[Depth; μ]*

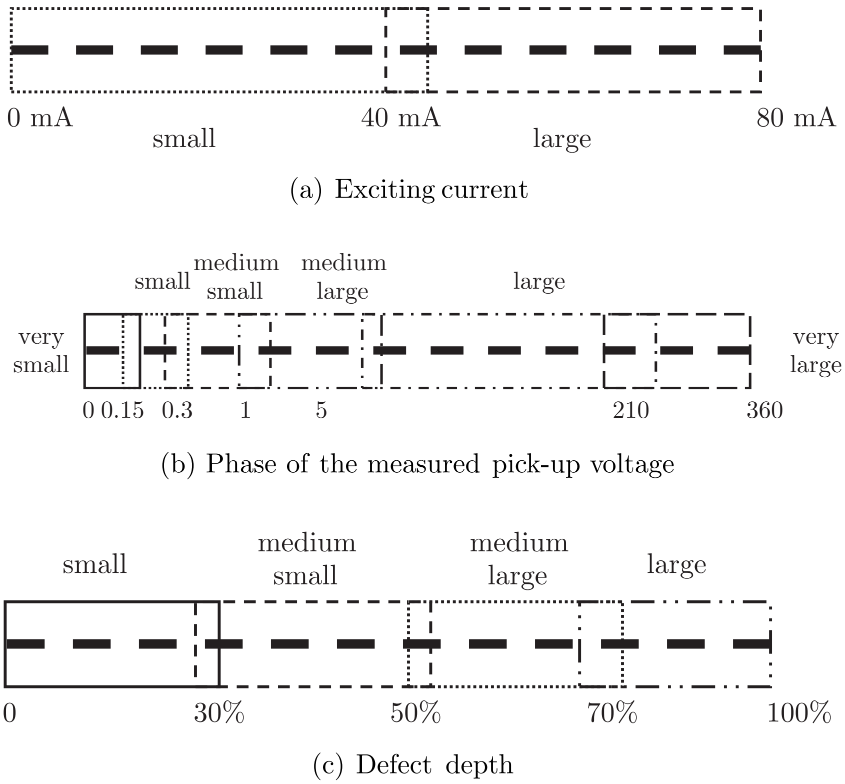


Figure 3. Representation of input-output set: a) exciting current; b) phase of the pick-up voltage; c) deepness of defect.

where μ^2 is the approximation of the "very" operator. In this way, due to the manipulation constraints, the number of rules obtained by CWs are lower than the ones obtained by a classical fuzzy subclustering. By using the Matlab© Fuzzy Toolbox, we have implemented a code allowing an automatic extraction of a bank of fuzzy rules with CWs. In order to emphasize the goodness of the obtained results, we have compared CWs and traditional fuzzy subclustering for the specimens under study. In particular, Table 2 summarizes the comparison in terms of accuracy for determining the correct defect depth. It is possible to denote how, for subsuperficial defects, CWs has a better behavior than fuzzy clustering. The error increases as in-depth location of the defect, up to becomes equal for CWs as well as for fuzzy subclustering. By the way, global results obtained with CWs are better than the ones obtained by fuzzy subclustering (Table 3).

Table 2. Errors (%) for each depth.

Defect depth (%)	Error with CWs (%)	Error with fuzzy subclustering (%)
20	0	3.85
40	2.93	3.8
60	4.34	5.15
100	5.85	5.85

Table 3. Comparison of global results between CWs and fuzzy subclustering.

Method	Global error (%)
CWs	3.281
Fuzzy subclustering	4.662

Table 4. Characteristic of best MFEFIS.

Minimal FE	No. of inputs	No. of outputs	No. of fuzzy rules
151.312	8	1	5

Table 5. Shape recognition results by using the best MFEFIS.

Specimen	Pattern	Kind of defect	Actual class	Estimated class
Rectangular steel plate	1	Cylindrical cavity	2	2
Multilayer steel plate	5	Hole	1	1
JSAEM	13	Crack	3	3
JSAEM	22	Crack	3	5

4.2. MFE for Defect Shape Recognition

The procedure has been applied to an array of {trainDB, testDB} databases' couples, built by mixing the collected 29 patterns. As described in the previous Section 3, each trainDB database is composed by 25 patterns, and the remaining 4 patterns (a cylindrical cavity-, a hole- and two rectangular-shaped defects) compose the testDB database. The best performances allowed to obtain a complete shape-recognition of the 3 differently shaped ECT testing: characteristics of related FIS retrieved by considering the MFE (MFEFIS) are resumed in Table 4.

5. CONCLUSIONS

In this paper, a novel approach for defects characterization in metallic plates is proposed. It examines flaws in terms of their depth and shape starting from a set of experimental measurements. Particularly, CWs have been taken into account to solve the problem of "multi-membership" of defects to several categories. An hybrid system based on CWs and MFE has been used. The former stage determines the defect's depth and quickly classify the results with low-computational complexity algorithms. Table 3 shows the global errors carried out by traditional fuzzy subclustering and CWs procedures. Let us remark how a CWs based fuzzy system has a lower computational complexity than a FIS obtained by using fuzzy subclustering. It is due to a sort of compaction of fuzzy rules carried out by CWs method.

Moreover, MFEFIS providing best shape-recognition performances has been able to detect in an exactly way the class of 3 testing defects (see Table 5). Wrong classification proposes an estimated class with a never-used codify: it should be solved by using a thresholding procedure on the MFEFIS outputs. Proposed experimentation shows a suitable use of Soft Computing approach in order to solve the inverse problem of flaw shape identification in metallic plates. In particular, use of Fuzzy Inference with the minimization of Fuzzy Entropy allowed to obtain a quick model, useful for real-time applications, having a low computational load. At the same time, proposed MFEFIS guarantees maintenance of useful information, avoiding to consider unnecessary features and so giving a good automatic solution or the "curse of dimensionality" problem.

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