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Mechanical Characterisation of thermal barrier coatings using a micro-indentation instrumented technique

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Abstract. An original instrumented microindenter capable of testing materials up to 1000°C in an inert atmosphere has been developed. The method of neural networks is used to solve the inverse problem, in order to determine the constitutive equation of the materials tested. To obtain a data basis for the training and validation of the neural network, finite element simulations were carried out for various sets of material parameters. To reduce the number of simulations a representative sampling of the loading-strain responses is performed using an unsupervised network, so-called self-organizing map.

Introduction

Thermal barrier coatings (TBCs) developed for protecting vanes and blades against the high temperature environment experienced in gas turbines, are multi-layer systems, each layer having a specific function. The ceramic layer - most generally yttria partially stabilized zirconia - used for the most demanding applications is deposited on a metallic bondcoat in contact with the superalloy substrate. They are exposed to a high temperature, hostile environment and must have a long and reliable life. The mechanical characterisation of the bond coat evolution (thickness around 50 μm) is important in understanding the durability and the performance of the overall thermal barrier. The composition and the microstructure of this bond coat evolve during service at high temperature, due to oxidation and interdiffusion phenomena. The micro-indentation technique appears as a technique particularly suitable for the study of such thin bond coats.

For a long time, the simplicity in performing a micro-indentation test was counter-balanced by the difficulty of quantitatively interpreting the results with more insight than with the hardness property. Recent experimental and modelling studies [1-3] of elasto-plastic indentation have shed light on the operating mechanisms and subsequent interpretation of the results. The characterisation at high temperatures of materials by instrumented indentation technique has been used by several groups to characterise the creep behaviour of various materials (for a review see for example Li [4]). Pioneering works by Mulhearn and Tabbor [5] and Atkins *et al* [6] have pointed out several pitfalls that may underlie the interpretation of data obtained from high temperature indentation tests. However, more recently, Dorner et al [7] have shown that it is possible to obtain creep laws comparable with those delivered by usual uniaxial tests. In the present paper, a micro-indentation device capable of testing materials up to 1000°C has been developed and used to identify at high temperature a complete elasto-visco-plastic constitutive equation on a NiAl(Pt) alloy whose composition is representative of materials constituting bond coat of thermal barrier coatings. The inverse problem of leading the depth-load response back to the related parameters in the constitutive equation is solved here using a neural network.

High temperature instrumented microindenter

The configuration and a view of the equipment are shown in the following figure. It comprises a vacuum chamber containing two translation tables (along horizontal X and Y axis) on which the load sensor, the sample holder, the sample and a furnace are fixed. The load is measured

with strain gage sensors and the test device is equipped with a data acquisition system. The maximum load is 3N and typical loading rates are $10^{-3} N.s^{-1}$. Pure argon (Argon C, 3ppm 0_2, 3ppm $H_2 0$) is used inside the chamber to maintain a neutral atmosphere during the high temperature tests. A primary vacuum (5.10^{-2} Pa) can be obtained with a Roots pumping system associated with a turbomolecular pump. The displacements are measured using the differential capacitive technology. A Vickers diamond sharp indenter with a face angle of 136° is used to progressively indent the surface of constituents of thermal barrier coatings.

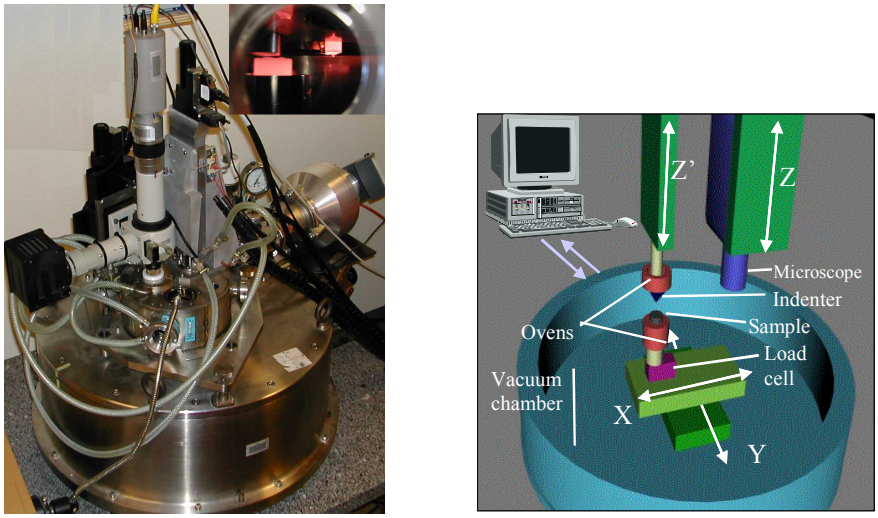

Fig. 1: Instrumented microindentation equipment for experiments up to 1000°C.

The available measurements include the simple Vickers hardness (Fig.2) and the force-penetration responses under simple (Fig.3) or complex (Fig.6) load histories. The load-displacement curves are obtained with a feedback control either on the load or on the displacement signal. The control on the load provides a feedback to reach the desired value directly on the piezoelectric translation table which increments the indenter displacement according to a convergence series.

Constitutive equations and definitions of the virtual experiments

In order to interpret the test results, a work of modelling has been performed allowing extracting, using a neural network, the mechanical properties of $\beta - NiAl(Pt)$ alloy. When studying indentation tests for elastic plastics solids, in most cases in the literature, the material is assumed to exhibit only isotropic hardening and a Ramberg-Osgood type law is used. The model used here is consistent with the unified viscoplastic formalism developed by Chaboche [5] which allows a unified description of yielding, creep, stress relaxation and a variety of other mechanical effects, such as Bauschinger effects and time recovery. The corresponding constitutive equations are listed in Table 1. The strain is assumed to be composed of elastic and inelastic parts as written in equation 1. An elastic domain is assumed, written in the stress space by means of the thermodynamic forces associated with the internal variables. For an isotropic material, the distance in the stress space is formulated using the Von Mises criterion given by equation (2) where σ_y is the true elasticity limit. In this expression, the back stress tensor X associated to the variables α_i gives the position of the elastic domain. σ' and X' are the deviators of the stress and the back stress tensors respectively. The kinematic hardening results from the superposition of several independent variables α_i which evolution laws are given by the combination of a static a static recovery term and a dynamic recovery term, as written in equation (5) where C_i and D_i are material parameters.

Table 1. The set of equations of the constitutive model. The MacCauley brackets in equation (7) are defined by $< u >= u$ if $u \geq 0$ or $< u >= 0$ if $u \leq 0$.

$\varepsilon = \varepsilon_e + \varepsilon_p$ (1)	Partition law
$f = J(\sigma - X) - \sigma_y \leq 0$ (2)	Von Mises material $J = \left[\frac{3}{2}(\sigma'_{ij} - X'_{ij})(\sigma'_{ij} - X'_{ij})\right]^{\frac{1}{2}}$ (3)
$X = \sum_{i=1}^{M} X_i = \frac{2}{3}\sum_{i=1}^{M} C_i \alpha_i$ (4)	Kinematical hardening $\dot{\alpha}_i = \dot{\varepsilon}_p - D_i \alpha_i \dot{p}$ (5)
$\dot{\varepsilon}_p = \dot{p}\frac{3}{2}\frac{\sigma' - X'}{\|\sigma - X\|}$ (6)	Viscoplastic flow $\dot{p} = \left\langle \frac{f}{\sigma_d} \right\rangle^n$ (7)

To characterise these material parameters, a training neural network is then used. A neural network is a parallel information processing array based on a network of interconnected artificial neurons (also called cells, units, nodes, or processing elements). The connections between the network elements have weights associated with them (which act as multipliers on the signal being transmitted), and the values of these weights are where the network model is stored. Each neuron has a transfer function and bias that relates its inputs to its output. The ability of the network to associate a particular output with an input pattern is a result of the training operations. To create the sample data set for the training, we have chosen a variety of constitutive laws defined by several set of material parameters $\{\sigma_y, C_1, C_2, C_3\}$ and then simulated using a finite element analysis the load-depth response to a micro-indentation test. However, if we explore uniformly the space of the parameters of a constitutive law, the induced strain-load responses are not uniformly distributed because of the non-linear character of such law. An unsupervised neural network, so called self-organizing map [7] has then been used to realise a representative sampling of the possible behaviours. 90 virtual materials have been then considered.

Indentation simulations and training of the neural network

The modelling of the indentation test by finite element analysis has then been undertaken using the Zebulon code developed at Onera and the School of Mines, Paris. In this study the three-dimensional indentation induced via Vickers geometry was approximated with an axisymmetric two-dimensional model. The mesh design for axisymmetric calculations is shown figure 4. In the finite element calculations, the indenter was modelled either as a diamond or a ruby body and the contact as frictionless. Moreover, the calculations were performed with the large deformation assumption. Each calculation consists of a simulation of cycling Vickers indentation tests.

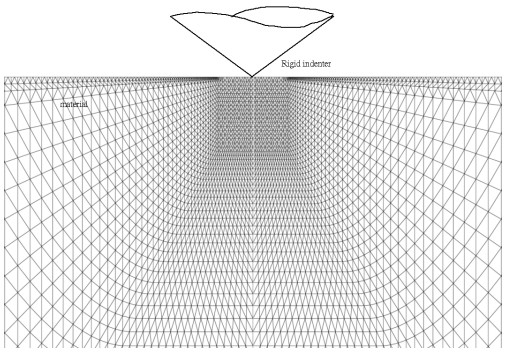

Fig. 2: The Finite Element Mesh

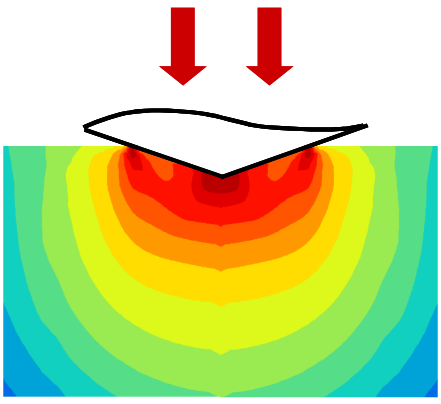

Fig. 3: Contour plot of the equivalent plastic strain within the 7075-T651 aluminium

The finite element model has been validated by comparisons to available FEM simulations in the literature. For each set of material parameters, the characteristic of the simulated indentation response is given to the neural network in order to learn the relation between the behaviour and the corresponding load-depth response. A decomposition of the complete response obtained by the finite element calculation is then made using the Principal Component Analysis (Fukunaga). The error in the decomposition is related to the number of chosen components. For our work, a selection of 10 principal components has been enough to finely reproduce all the simulated load-depth responses. Different types of neural network have evolved based on the neuron arrangement, their interconnections and training paradigm used. In our work is used an hybrid approach cumulating the advantages of the "kriging" interpolation technique and the "MLP regression" one. The training pattern is performed with 50 set of material parameters and corresponding simulations. The 40 left are used for the validation of the network. In order to illustrate the identification capabilities of the network, the exact and the identified value of the 0.2% yield stress is compared in the figure 4 for the validation patterns. It can then be observed that the neural network provides an excellent identification. The application of the inverse method to indentation tests allows obtaining a good estimation of the NialPt parameters as it can be observed in the figure 5.

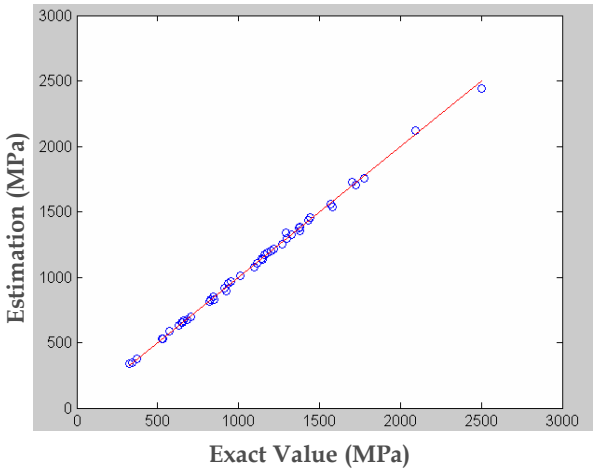

Fig.4: Diagram of the dispersion showing the error in the prediction of the 0.2% yield stress for the validation patterns.

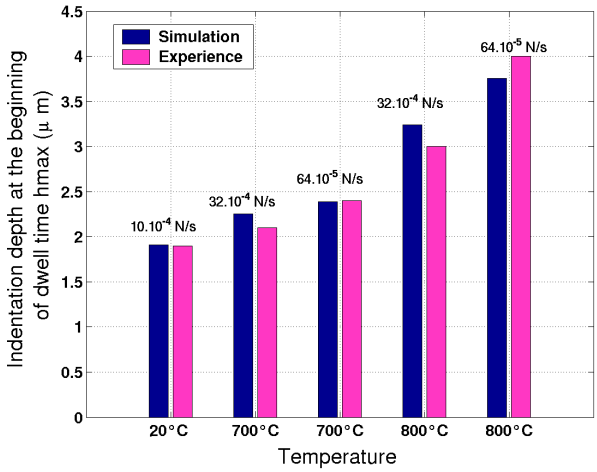

Fig.5: Experimental versus computational indentation depth at the beginning of dwell time of indentation tests with dwell time performed at two loading rates

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