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Modelling of the rheological behaviour of aluminium alloys in multistep hot deformation using the multiple regression analysis and artificial neural network techniques

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Abstract

Artificial neural network and multiple regression analysis techniques were applied in modelling the rheological behaviour of AA 6082 aluminium alloy under multistep hot deformation conditions. To this end, multistage torsion tests were carried out in order to obtain the experimental data to be used in the development of the predictive models. The envelope curves predicted by both the ANN- and MRA-based models have shown an excellent fit, in terms of curve shape and stress level, with the experimental ones obtained under the same process conditions, even if the ANN based model has provided the best predictive capability.

Keywords: Multistep deformation test; Artificial neural network; Multiple regression analysis; Flow modelling

1. Introduction

The large amount of deformation applied and the significant changes in the workpiece shape occurring during the most of metal-forming operations lead to the need to apply complex forming routes including several deformation stages. Since the restoration mechanisms taking place during each deformation step and between two succeeding steps are related to the thermo-mechanical history of the deforming material, the hot working behaviour must be investigated under multistep deformation conditions. To this purpose, laboratory tests, such as compression and torsion tests [1–3], allow the analysis, for each deformation step, of the influence of the process parameters, such as temperature, strain and strain rate, time between two succeeding steps, etc. on both the rheological behaviour and microstructure [1].

There are different categories of rheological models, according to the relationship between flow stress and process parameters [4]; among them, the models using empirically derived equations are largely applied because they allow to develop general procedures for calculating flow stress data without knowing a priori which microstructural mechanisms may be operating during the deformation process [5]. In this framework, the multiple regression analysis (MRA) approach, in which the values of a dependent variable are analytically described in terms of at least two independent variables, can be effectively used [6–8].

An emerging approach that allow to overcome the difficulty arising in the assessment of the complex relationships that are on the basis of empirical analytical models, is based on the empirical non-analytical models, such as artificial neural networks. An artificial neural network (ANN) solves a problem by learning rather than by a specific programming based on well-defined rules [2,9–12]. Many researchers applied the ANN-based models to predict flow curves in a single step deformation on several materials [2,3,9,13], whilst a limited number of applications concerning the prediction of the stress–strain curves in multistep deformation can be found, mainly in two-steps compression tests [3].

In metal forming operations with a multistage schedule of several passes, such as hot rolling, the process parameters can undergo severe variations from the initial to the final stage that can lead to large changes in flow stress, much higher than those occurring during each deformation step. In such conditions, the rheological models can be used to predict the envelope curve, obtained through the flow curve maxima of each pass, instead of the flow curve of each pass, since it gives a direct evidence of the effect of dynamic and static parameters, controlling the multistage deformation process, on flow stress.

In this framework, the response of AA 6082 aluminium alloy under multistep hot deformation conditions, in terms of envelope

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Table 1
Experimental conditions of multistage torsion tests

T (°C)	$\dot{\varepsilon}$ (s^{-1})	ε_p	t_p (s)
Decreasing ($525 \rightarrow 300$)	Constant (0.3/3)	Constant (0.2/0.4)	Constant (20/300)
	Increasing ($0.3 \rightarrow 3$), ($1 \rightarrow 3$)	Constant (0.2/0.4)	Constant (20/300)
	Increasing ($0.3 \rightarrow 3$)	Decreasing ($0.8 \rightarrow 0.2$), ($1 \rightarrow 0.2$)	Constant (20/300)

curve, was modelled using both MRA- and ANN-based techniques. The ability of models to capture the effects of dynamic and static process parameters on the envelope curves was widely investigated.

2. Material and experimental procedures

2.1. Multistep hot deformation tests

The rheological behaviour of AA 6082 aluminium alloy was studied by multistage torsion tests performed on an electrically-powered servo-controlled torsion testing machine. Details on the initial temper state of material, sample geometry, heating and cooling procedures can be found in [14,15]. The different test procedures and the experimental conditions are shown in Table 1. The time between two subsequent deformation steps (t_p), the equivalent strain per pass (ε_p), the equivalent strain rate ($\dot{\varepsilon}$) and temperature (T) were chosen with the aim of approaching the process conditions taking place during complex forming cycles [1].

2.2. ANN and MRA analyses

The material response under multistep hot deformation was modelled using two different approaches based on ANN and MRA techniques. In the ANN-based approach, a multi-layer feed forward ANN, using the back-propagation algorithm, was built [2,3]. Nine inputs were chosen, closely related to the process parameters of multistep deformation [3,9]: T, ε, $\dot{\varepsilon}$, t_p, ε_p, $\ln \varepsilon$, $\ln \dot{\varepsilon}$, $1/T$ and D_0, where D_0 is the initial grain size [3]. The outputs of the ANN were the flow stress, in terms of envelope curve through the flow curve maxima of each pass, and the flow stress as logarithmic function. The final network configuration consisted of one hidden layer with nine hidden neurons. The topology and training parameters for the developed artificial neural network-based models are shown in Table 2.

In the MRA-based approach, the dependent variable (σ) was related to the independent variables (ε, T, $\dot{\varepsilon}$, t_p, ε_p, D_0) using both first (linear) and second (polynomial) order regression models. The results obtained have shown that no substantial improvement is given by the polynomial regression so that the linear regression-based approach was used. As a consequence, the flow stress values, in terms of envelope curves, were predicted using the following relationship:

$$\sigma_i = a + b_i\varepsilon + c_i T + d_i\dot{\varepsilon} + e_i t_p + f_i\varepsilon_p + g_i D_0 \quad i = 1, 2, \ldots, n$$

where a, b, c, d, e, f and g are the regression coefficients, and n is the number of steps.

Table 2
Topology and training parameters for the developed artificial neural network

Number of input nodes (T, ε, $\dot{\varepsilon}$, t_p, ε_p, $\ln \varepsilon$, $\ln \dot{\varepsilon}$, $1/T$, D_0)	9
Number of output nodes (σ, $\ln \sigma$)	2
Number of hidden layers	1
Number of hidden nodes	9
Activation function input-hidden layers	Sigmoid
Activation function hidden-output layers	Linear
Distribution of weights	Gaussian
Momentum coefficient	0.1
Learning coefficient	0.9

The effectiveness of both approaches in modelling the rheological behaviour under multistage hot deformation conditions was proven using the "leave-k-out" method [16].

3. Results and discussion

The effects of dynamic and static control parameters on the experimental flow curves of AA 6082 aluminium alloy and on the envelope curves predicted using both the ANN- and MRA-based models are shown in Figs. 1–5. In particular, it can be seen:

- temperature (Figs. 1–5) and strain rate (Figs. 1 and 2) affect the flow stress according to the behaviour exhibited during monotonic hot deformation [14,15,17];
- the flow stress is affected by the strain rate path (Fig. 2), due to the strong influence of temperature on the constitutive parameters [15];
- the time between two subsequent deformation steps influences the flow stress (Fig. 3) by leading to a decrease in σ with increasing t_p, owing to the static restoration mechanisms occurring during each rest period [15];
- the flow stress is not significantly affected by ε_p at high temperatures whilst, at low temperatures, a decrease in ε_p produces a slight decrease in σ value (Fig. 4). Such behaviour, that seems to be in contrast with that expected for the effect of ε_p alone, can be related to the increase in the number of

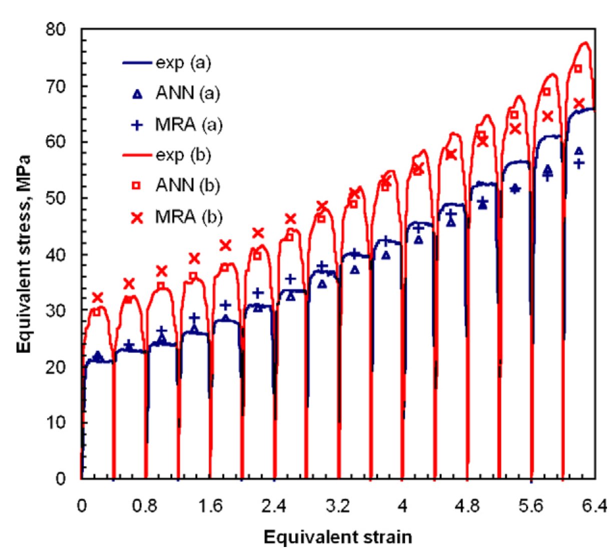

Fig. 1. Effect of strain rate on the experimental flow curve and predicted envelope curves ($T = 525 \rightarrow 300$ °C; $t_p = 20$ s; $\varepsilon_p = 0.4$): $\dot{\varepsilon} = 0.3\ s^{-1}$ (a) and $\dot{\varepsilon} = 3\ s^{-1}$ (b).