Intelligent Material Modelling for Mild Steel Hot Working

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In this paper, neural network based constitutive models relating stress to deformation conditions of mild steel subjected to hot forging is attempted through a parallel distributed processing paradigm based on artificial neural network prediction of the metal material response. Laboratory data of the stress-strain behaviour of the mild steel subjected to compression tests with different temperature and strain rate conditions were utilized to evaluate different feed-forward back-propagation neural network models for flow stress prediction. The results obtained displayed a good agreement with the experimental data, showing that the neural network approach can accurately describe the material flow stress under the considered processing conditions.

1. INTRODUCTION

In the last two decades, many attempts have been made to model the rheological behaviour of metals under hot forging conditions [1, 2]. The hot strength of a material during hot forging is the measure of the material resistance to the imposed deformation conditions; this parameter is critical in the development of a model for hot forging force evaluation and is the subject of the present work. To date, the rheological behaviour of hot forged metals is represented through constitutive equations, where the material response is correlated only to the instantaneous values of process parameters (strain, strain rate, temperature). Even under this approximation of operating conditions, the definition of correct analytical relation-ships involves the complete understanding of all the phenomena influencing the instantaneous material response (strain hardening, dynamic recovery, recrystallisation) that, particularly in hot forging, are very complex and not easy to model. More recently, the introduction of artificial neural networks (NNs) has led to alternative models being proposed to predict the flow stress of various materials [3-8]. The main objective of this work is to identify a reliable and easy to use tool to represent the rheological data even under deformation conditions where not all the parameters contributing to the definition of the material rheological behaviour are well known. To this scope, a parallel distributed processing approach, based on feed-forward back-propagation NNs, is employed to model and reconstruct the rheological behaviour of metals under hot deformation conditions, typical of industrial hot forging processes.

2. MATERIAL AND EXPERIMENTAL TESTS

The evaluation of the NN models for flow stress prediction was carried out on the basis of laboratory data of the stress-strain behaviour of a mild steel material subjected to compression tests with different temperature and strain rate conditions. The mild steel composition was: C 0.16, Mn 0.63, Si 0.33, Ni 0.24, Cr 0.16, Mo 0.04, Cu 0.17, Al 0.05, S 0.047, P 0.011.

The hot compression test results considered in this paper were retrieved from Ponthot's Metal Benchmark available in the Esaform official web-site: www.esaform.com [9]. Hot compression tests were carried out at different constant values of temperature and strain-rate, with the aim of evaluating the material sensitivity to process parameters variations. The initial room temperature geometry and the final geometry after cooling down to room temperature are reported in Table 1 for the hot compression samples taken into consideration.

The sample geometrical dimensions were measured at room temperature and modified through the linear coefficients of thermal expansion in Table 2 to refer to the actual test temperatures. Three thermal conditions were considered for testing: 950 °C, 1050 °C and 1150 °C. The temperature conditions were assumed to be constant during the whole test. The testing machine cross-head speed was set up to provide a quasi-constant strain rate. The selected values for strain rate were: 0.02 s^{-1}, 0.5 s^{-1} and 5.0 s^{-1}.

During each hot compression test, reported in Table 1, experimental data were sampled from the stress-strain curve and a curve vector consisting in a sequence of data points, each identified by a stress value, σ, and its corresponding strain value, ε, was generated. The number of curve data points depends on the time duration of each hot compression test. The set of the 7 curve vectors made up the training set for NN processing.

Figure 1 shows some examples of the experimental curves, exhibiting a peak stress after work hardening at low strains followed by gradual work softening towards steady state.

3. NEURAL NETWORK DATA PROCESSING

Different 3-layered feed-forward back-propagation NNs were trained and tested to produce a mapping from input vectors to output values, in order to model the material response to hot forging process conditions, The inputs to the NN were chosen to be the parameters that define the physical meaning of the process.

Table 1:

Summary of hot compression tests.

h_0 = initial height, d_0 = initial diameter,

h_f = final height,

d_f = final diameter.

Test id.	h_0 (mm)	d_0 (mm)	h_f (mm)	d_f (mm)	Temperature (°C)	Strain rate (s^{-1})	# of curve data points
125A	20.10	13.14	10.19	19.76	950	0.02	2328
135A	20.31	13.22	10.29	19.79	1150	0.02	2323
315A	20.18	13.13	10.18	19.43	950	0.50	494
325B	20.23	13.21	10.37	19.64	1050	0.50	493
515B	20.10	13.14	10.06	19.66	950	5.00	497
525A	20.25	13.16	10.23	19.73	1050	5.00	499
535A	20.26	13.16	10.25	19.74	1150	5.00	299

Table 2:

Linear coefficients of thermal expansion.

Temperature (°C)	Alpha
from 20 °C to 872.5 °C	13*10-6
from 872.5 °C to 904.4 °C	-56*10-6
from 904.4 °C to 1200 °C	26*10-6

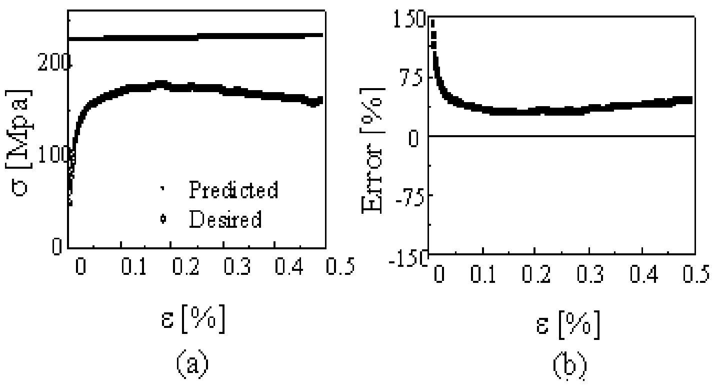

Figure 1:

Experimental stress-strain curves at T = 950 °C and various strain rate values.

Table 3:

NN configurations.

ε = strain;

$\dot{\varepsilon}$ = strain-rate;

T = temperature;

ε_p = peak strain;

σ = flow stress.

NN configuration	Input vector	Output vector
3-3-1	$\{\varepsilon, \dot{\varepsilon}, T\}$	σ
4-3-1	$\{\varepsilon, \dot{\varepsilon}, T, \varepsilon_p\}$	σ
6-3-1	$\{\varepsilon, \dot{\varepsilon}, T, \ln(\varepsilon), \ln(\dot{\varepsilon}), 1/T\}$	σ
7-3-1	$\{\varepsilon, \dot{\varepsilon}, T, \ln(\varepsilon), \ln(\dot{\varepsilon}), 1/T, \varepsilon_p\}$	σ

The inputs to the NN were chosen to be the parameters that define the physical meaning of the process. Strain, strain-rate and temperature values for each experimental curve were always utilised as input features. In some NN configurations, also strain and strain-rate as logarithmic functions, $\ln(\varepsilon)$ and $\ln(\dot{\varepsilon})$, temperature as inverse function, 1/T, and curve peak strain (strain value for which flow stress is maximum in the stress-strain curve), ε_p, were employed as input features. This was accomplished to take into account the analytical relationships existing among the considered process parameters [4, 5] and the influence of curve peak strain on the material behaviour modelling [10].

The various NN configurations (Table 3) had a number of nodes in the input layer equal to the number of features in the input vector. In all configurations, the hidden layer had 3 nodes, determined by the "cascade learning" procedure [11], and the output layer 1 node for flow stress prediction. NN training was carried out by the "leave-k-out" method, particularly useful when dealing with small training sets: one curve vector (k = 1) was held back in turn for the testing phase and the other curve vectors were used for training.

The strain value of single data points from each curve vector, together with curve and process parameters, were sequentially presented to the NN input layer and the corresponding flow stress was fed to the output layer for NN training, following the procedure reported in [11]. During NN testing, the complete stress-strain curve for a given test condition was reconstructed and the error was evaluated by comparison with the experimental curve.

Test id.	Curve RMS error			
	3-3-1 NN	4-3-1 NN	6-3-1 NN	7-3-1 NN
125A	15.3	7.6	12.1	6.5
135A	51.8	30.3	48.3	27.8
315A	65.2	15.1	57.6	12.7
325B	83.6	46.7	48.9	29.0
515B	83.6	48.1	76.9	31.7
525A	27.1	16.1	23.2	9.7
535A	28.3	18.8	20.1	15.9

Table 4:

Performance of the different NN configurations in terms of curve RMS error.

4. FLOW STRESS PREDICTION

4.1. 3-3-1 NN configuration

Three-component input vectors including strain, constant strain-rate and constant temperature {ε, &, T} were used for training and testing the 3-3-1 NN configuration. Desired flow stress σ, predicted flow stress σ_{pred}, yielded by the learned 3-3-1 NN, and percent error

E% = (σ_{pred} - σ)/ σ_{pred} were plotted versus strain. The curve RMS error was evaluated and reported in Table 4.

Figure 2 reports a typical 3-3-1 NN response for the reconstruction of the stress-strain curve of test 315A. From the figure, it can be seen that curve reconstruction is very poor in terms of both curve geometry (the reconstructed curve is a straight line) and flow stress values (the predicted flow stress is much higher than the actual one).

Accordingly, the curve RMS error is as high as 65.2. The 3-3-1 NN is unable to predict both the steep variation of stress with strain at low strains in the work hardening region and the gradual work softening after peak stress in the recrystallisation region.

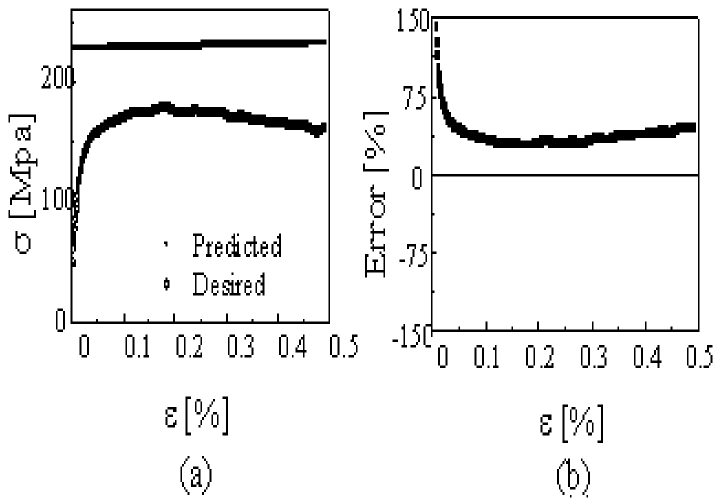

Figure 2:

3-3-1 NN configuration using input vectors {ε, &, T} Test 315A.

(a) Desired and predicted flow stress vs. strain;

(b) flow stress percent error vs. strain.

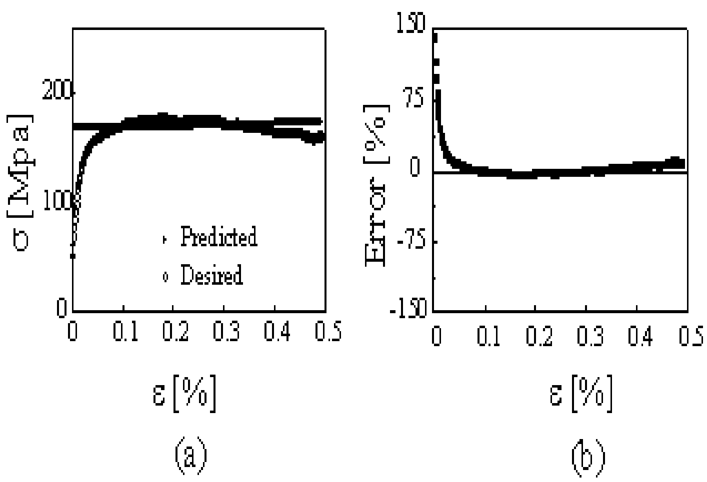

Figure 3:

4-3-1 NN configuration using input vectors {ε, &, T, ε_p} Test 315A.

(a) Desired and predicted flow stress vs. strain;

(b) flow stress percent error vs. strain.

4.2. 4-3-1 NN configuration

To consider the influence of characteristic experimental curve features on the material behaviour modelling, curve peak strain ε_p was added to the input features and 4-component input vectors {ε, &, T, ε_p} were used for training and testing the 4-3-1 NN. The ε_p value utilised in the leave-k-out NN training and testing was obtained by averaging the ε_p values of the curves available for

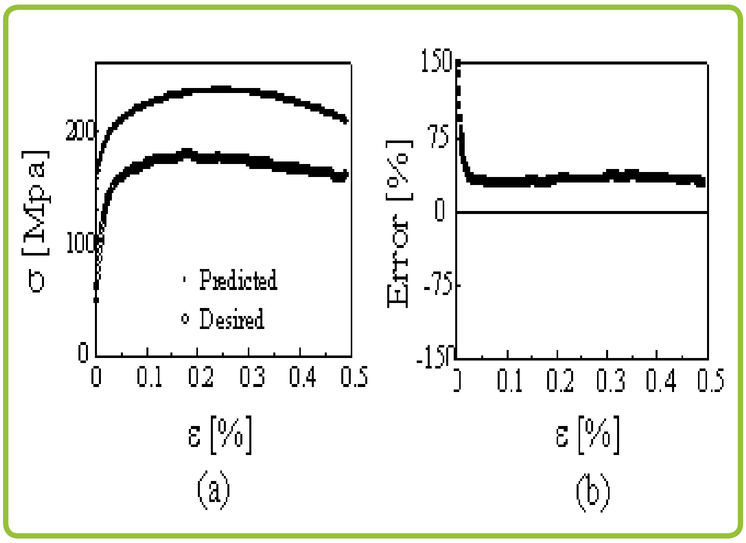

Figure 4:

6-3-1 NN config. using input vectors $\{\varepsilon, \dot{\varepsilon}, T, \ln(\varepsilon), \ln(\dot{\varepsilon}), 1/T\}$ Test 315A.

(a) Desired and predicted flow stress vs. strain;

(b) flow stress percent error vs. strain.

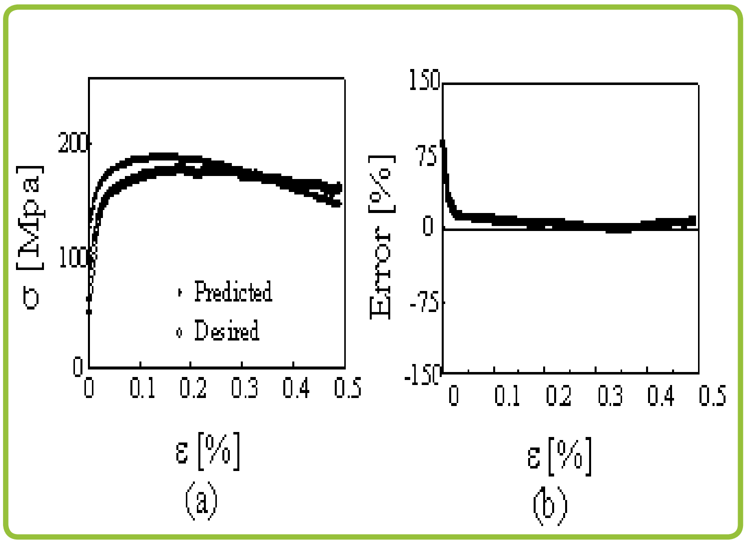

Figure 5:

7-3-1 NN config. using input vectors $\{\varepsilon, \dot{\varepsilon}, T, \ln(\varepsilon), \ln(\dot{\varepsilon}), 1/T, \varepsilon_p\}$ Test 315A.

(a) Desired and predicted flow stress vs. strain;

(b) flow stress percent error vs. strain

training, i.e. all curves but the one left out for testing. This procedure was adopted because the ε_p values for the available training set did not show any dependence on temperature or strain-rate in the considered variation ranges. Desired flow stress σ, predicted flow stress σ_{pred} and percent error E% were plotted versus strain. The curve RMS error was evaluated and reported in Table 4. In Figure 3, the flow stress and error curves for test 315A are shown. Curve reconstruction is still poor in terms of curve geometry (the reconstructed curve is still a straight line) but the predicted flow stress is very close to the actual one, at least at large strains. Accordingly, the curve RMS error is as low as 15.1. Also the 4-3-1 NN is unable to predict the work hardening and work softening material behaviour. However the addition of p seems to provide the NN model with information useful to reduce the offset between predicted and desired flow stress values, at least in the steady state region.

4.3. 6-3-1 NN configuration

To take into account the analytical relationship among the considered process parameters, 6-component input vectors including the logarithmic functions of ε and $\dot{\varepsilon}$ and the inverse function of T, $\{\varepsilon, \dot{\varepsilon}, T, \ln(\varepsilon), \ln(\dot{\varepsilon}), 1/T\}$, were used for training and testing the 6-3-1 NN. Desired flow stress σ, predicted flow stress σ_{pred} and percent error E% were plotted versus strain. The curve RMS error was evaluated and reported in Table 4. In Figure 4, the flow stress and error curves for test 315A are shown. At least on a qualitative basis, the work hardening and the dynamic recrystallisation regions are reproduced by the predicted curve. The curve RMS error is however high, achieving 57.6. The addition of the logarithmic functions of strain and strain-rate and the inverse function of temperature appears to provide the NN model with information critical for material behaviour modelling, at least on a qualitative basis. The 6-3-1 NN seems able to model the work hardening and work softening material behaviours, although the general curve offset is still high.

4.4. 7-3-1 NN configuration

To further improve the information content of the NN input, curve peak strain ε_p was added to the input features to construct the 7-component input vectors $\{\varepsilon, \dot{\varepsilon}, T, \ln(\varepsilon), \ln(\varepsilon), 1/T, \varepsilon_p\}$ used for training and testing the 7-3-1 NN. Desired flow stress σ, predicted flow stress σ_{pred} and percent error E% were plotted versus strain. The curve RMS error was evaluated and reported in Table 4. In Figure 5, the flow stress and error curves for test 315A are shown.

A generally good fit is verified both in the work hardening and the work softening regions. Accordingly, the curve RMS error is reduced to 12.7. The 7-3-1 NN gives a much better agreement with experimental data than all the previous NN configurations examined, providing more accurate predictions in the full region of the stress-strain curve, from work hardening to dynamic recrystallisation of the mild steel material. The presence in the input vectors of features accounting for both the analytical relationships existing among the process parameters and the influence of peak strain on the material behaviour modelling allowed for an accurate description of the mild steel material flow stress under hot forging conditions.

5. CONCLUSIONS

Modelling of the rheological behaviour of a mild steel under hot deformation conditions, typical of industrial hot forging processes, was carried out through flow stress prediction using different feed-forward back-propagation NN configurations. The evaluation of the NN performance was performed on the basis of laboratory data on the stress-strain behaviour of mild steel subjected to compression tests with variable temperature and strain-rate conditions. The results obtained by using only strain, strain-rate and temperature as NN input features did not allow for stress-strain curve reconstruction. In the case of input vectors containing features accounting for both the analytical relationships existing among the process parameters and the influence of peak strain on the material behaviour modelling, the NN could accurately describe the mild steel flow stress, under the considered processing conditions, in the full region of the stress-strain curve, from work hardening to dynamic recrystallisation.

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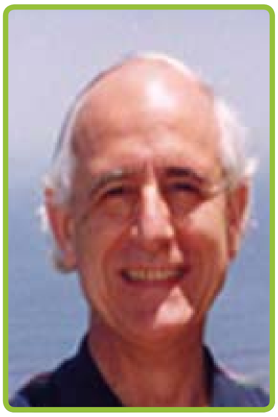

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