Material modelling for the simulation of microforming processes at elevated temperature

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Abstract

The main objectives of this paper are investigations on the usability of artificial neuronal networks for the calculation of material properties at elevated temperatures in case of microforming processes. Modelling of the rheological behaviour of diverse materials subjected to hot forging is attempted through a parallel distributed processing paradigm based on artificial neural network prediction of the metal material response. The evaluation of different feed-forward back-propagation neural networks for flow stress prediction was carried out on the basis of laboratory data of the stress-strain behaviour of nickel base superalloys and mild steel subjected to compression tests with different temperature and strain rate conditions. 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.

Keywords: Material modelling, High temperature, Microforming

1. Introduction

The main objective of the research activity illustrated in this paper is the investigation on the applicability of artificial neural networks for the modelling of the materials behaviour at elevated temperature in the case of microforming processes. This approach has recently shown its potential and its further deepening should lead to the required enhancement of process knowledge as well as to the improved capability for material properties evaluation necessary for developing simulation methods applicable at microscale level.

Intelligent computation tools with the goal of performing production engineering tasks must necessarily incorporate knowledge of the dynamics of the physical systems involved [1]. Such knowledge is properly represented by behavioural models which may be built from experimental data: the process of modelling from data may be performed either by using structural models or by learning input-output relationships directly from the data. The former approach is feasible whenever knowledge of the underlying physics is available, whereas the latter one is considered when the structural equations cannot be written because the knowledge about functional relationship is either incomplete or unknown or no first principles are available. The interpretation of observations and experimental data is a fundamental step in the model formulation process: the expert, given a set of observations, examines the shape of the plotted data and, on the basis of the highlighted properties, makes an initial guess for one or more models explaining the features of the data. It is worth emphasising that the knowledge available in the field of metal forming processes is often of a non deterministic type: it is well known that, in many cases, the "optimal" selection of process parameters in metal forming operations is largely based on human experience, which represents a kind of knowledge not easily transformed into explicit and deterministic form. These difficulties can be efficiently confronted by resorting to intelligent computing techniques such as fuzzy logic (FL), neural networks (NN) and neuro-fuzzy (NF) systems. FL is suitable when dealing with vague and imprecise knowledge, NN allow to process information coming from past experiences and deduce new knowledge, and NF systems represent a synergical combination of the two previous techniques [2].

In the last decades, many attempts have been made to model the rheological behaviour of metals under hot forming conditions [3]. To date, the rheological behaviour of hot formed metals is represented through constitutive equations, where the material response is correlated only to the istantaneous values of process parameters (strain, strain rate, temperature). Even under this approximation of operating conditions, the definition of correct analytical relationships involves the complete understanding of all the phenomena influencing the instantaneous material response (strain hardening, dynamic recovery, recrystallisation) that, particularly in hot forming, are very complex and not easy to model. 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. Recently, the introduction of artificial NN has led to innovative models being proposed to predict the flow stress of various metal materials [4]. In this paper the performance of different NN models applied to the accurate simulation and prediction of the flow stress of mild steel and nickel base superalloys under hot deformation conditions, typical of industrial hot forging processes are investigated and compared and the usability of artificial neuronal networks for the calculation of material properties at elevated temperatures is studied.

2. Materials 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 different materials: a mild steel and a nickel base superalloy (Nimonic 115) material subjected to compression tests with different temperature and strain rate conditions.

2.1. Mild steel

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 Prof. Ponthot's Metal Benchmark available in the Esaform official web-site: www.esaform.com [5]. 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 compression test indicated 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 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.

Table 1
Summary of hot compression tests of mild steel.
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 of mild steel.

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	$26*10^{-6}$

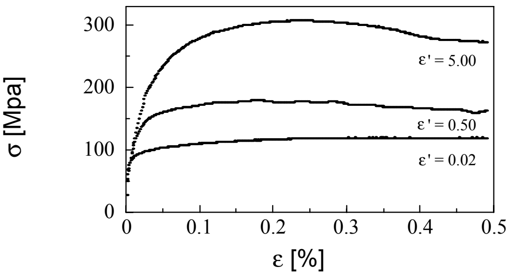

Fig. 1. Experimental stress-strain curves of mild steel at T = 950 °C and various strain rate values.

2.2. Nickel base superalloy: Nimonic 115

The Nimonic 115 nickel base superalloy, subjected to compression tests, is a Ni-Cr-Co base alloy, strengthened with additions of Mo (3.0 – 5.0 %), Al (4.5 – 5.5 %) and Ti (3.5 – 4.5%). Hot compression tests were carried out at different constant values of temperature and strain-rate to evaluate the material sensitivity to process parameters variations. Prior to testing, the Nimonic 115 alloy was submitted to a solution heat treatment: the material was heated up to 1190 °C, held at constant temperature for 90 minutes, and then still-air cooled. A total number of 9 valid compression tests were carried out on a computer-controlled dynamic system, Gleeble 2000®, equipped with Hidra-Wedge®. The cylindrical hot compression samples were mounted on the testing machine, heated up to the testing temperature at a rate of 5 °C/s, held at temperature for 30 s max to make the temperature uniform, and then compressed at constant strain-rate up to a maximum strain of 0.8%. Three thermal conditions were considered for testing: 110 °C, 1140 °C and 1180 °C. The selected values for constant strain rate were: 0.1 s^{-1}, 1.0 s^{-1} and 15.0 s^{-1}. During each compression test (Table 3) 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 set of the 9 curve vectors made up the training set for NN processing. Figure 2 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

To model the material response to hot forging process conditions, different 3-layered cascade-forward back-propagation NNs were trained and tested to produce a mapping from input vectors to output values. The inputs to the NN were the parameters that define the physical meaning of the process. Strain, strain-rate and temperature for each experimental curve were utilized as input features to construct 3-feature input vectors, {ε, $\dot{\varepsilon}$, T}. To take into account the analytical relationships among the considered process parameters [4] and the influence of curve peak strain on the material behaviour modelling [6], also strain and strain-rate as logarithmic function, ln(ε) and ln($\dot{\varepsilon}$), temperature as inverse function, 1/T, and curve peak strain, ε_p, were used as input features. Accordingly, 6-feature and 7-feature input vectors were built: {ε, $\dot{\varepsilon}$, T, ln(ε), ln($\dot{\varepsilon}$), 1/T, ε_p}, respectively. The various NN configurations (Table 4), had a different number of nodes in the input layer according to the number of features in the input vector. In all configurations, the hidden layer had 3 nodes 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. The curve vectors were fed to the NN input layer to obtain the predicted flow stress from the NN output layer. Single data points from each curve vector were utilized for NN training and testing. The strain value of each data point, together with further curve and process parameters, were sequentially presented as input features to the NN input layer and the corresponding flow stress was fed to the output layer for NN training. During NN testing, the complete stress-strain curve for a given test condition is reconstructed and the error is evaluated by comparison with the actual experimental curve.

3.1. Mild steel
7-3-1 NN configuration

7-component input vectors including strain, constant strain-rate, temperature, logarithmic function, ln(ε), ln($\dot{\varepsilon}$), temperature as inverse function, 1/T, and curve peak strain, ε_p, {ε, $\dot{\varepsilon}$, T, ln(ε), ln($\dot{\varepsilon}$), 1/T, ε_p} were used for training and testing the 7-3-1 NN. Desired flow stress σ, predicted flow stress σ_{pred} and percent error E% = (σ_{pred} - σ)/σ_{pred} were plotted versus strain. In Figure 3, the flow stress and error curves for test 315A are shown.

Table 3
Summary of hot compression tests of Nimonic 115.

Test id.	Temperature [°C]	Strain rate [s^{-1}]	# of curve data points
1	1100	0.1	80
2	1100	1.0	79
3	1100	15.0	79
4	1140	0.1	73
5	1140	1.0	74
6	1140	15.0	81
7	1180	0.1	150
8	1180	1.0	74
9	1180	15.0	74

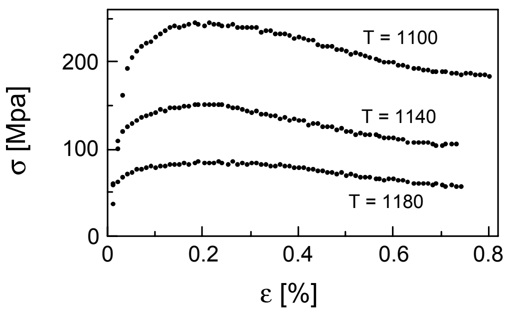

Fig. 2. Experimental stress-strain curves of Nimonic 115 for $\dot{\varepsilon}$ = 0.1 s-1 and different temperatures.

Table 4: 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	{ε, $\dot{\varepsilon}$, T}	σ
6-3-1	{ε, $\dot{\varepsilon}$, T, ln(ε), ln($\dot{\varepsilon}$), 1/T}	σ
7-3-1	{ε, $\dot{\varepsilon}$, T, ln(ε), ln($\dot{\varepsilon}$), 1/T, ε_p}	σ

Table 5
Performance of the NN configurations in terms of curve RMS error. (a) mild steel; (b) Nimonic 115.

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

(a)

Test n.	Curve RMS error		
	3-3-1 NN	6-3-1 NN	7-3-1 NN
1	14.9	11.0	6.3
2	26.6	25.7	15.9
3	100.9	82.3	28.7
4	21.1	19.1	4.8
5	27.2	15.6	9.7
6	68.7	41.1	19.9
7	34.2	22.2	7.3
8	20.1	14.9	5.0
9	51.5	29.8	15.1

(b)

The curve RMS error was evaluated and reported in Table 5a. 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.

3.2. Nimonic 115
7-3-1 NN configuration

7-component input vectors including strain, constant strain-rate, temperature, logarithmic function, ln(ε), ln($\dot{\varepsilon}$), temperature as inverse function, 1/T, and curve peak strain, ε_p, {ε, $\dot{\varepsilon}$, T, ln(ε), ln($\dot{\varepsilon}$), 1/T, ε_p} were used for training and testing the 7-3-1 NN. The ε_p value utilized in the leave-k-out NN training and testing phases was obtained by averaging the p values of the curves available for 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. The desired flow stress σ, the predicted flow stress, σ_{pred}, yielded by the learned 7-3-1 NN, and the percent error E% = (σ_{pred} - σ)/σ_{pred} were plotted versus strain. The RMS error for the predicted curves was evaluated and reported in Table 5b. Figure 4 reports the 7-3-1 NN response for Test n. 5 (T = 1140 °C, $\dot{\varepsilon}$ = 1.0 s^{-1}). From the figure, it can be observed that a generally good fit is verified both in the work hardening and the work softening regions. Accordingly, the curve RMS error is reduced to 9.7 (Table 5b). The 7-3-1 NN configuration gives a much better agreement with experimental data than 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 nickel base alloy material.

4. Conclusions

Modelling of the rheological behaviour of a mild steel and a nickel base superalloy 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 the two materials subjected to compression tests with variable temperature and strain-rate conditions. 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 actually allowed for an accurate description of both metals flow stress under hot forging conditions. The implementation of NN based approach for the modelling of the material behaviour in forming at high temperature can provide the required enhancement of process knowledge as well as to the improved capability for material properties evaluation necessary for developing simulation methods applicable at microscale level.

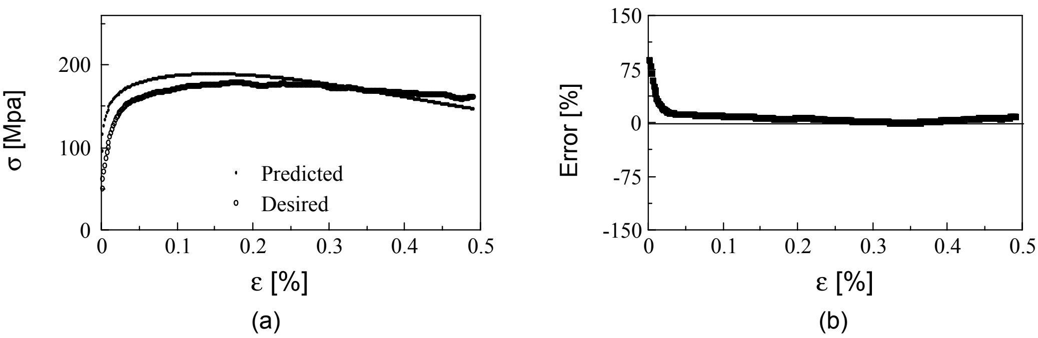

Fig. 3. 7-3-1 NN config. using input vectors {ε, $\dot{\varepsilon}$, T, ln(ε), ln($\dot{\varepsilon}$), 1/T, ε_p}. Test 315A: mild steel: (a) Desired and predicted flow stress vs. strain; (b) flow stress percent error vs. strain.

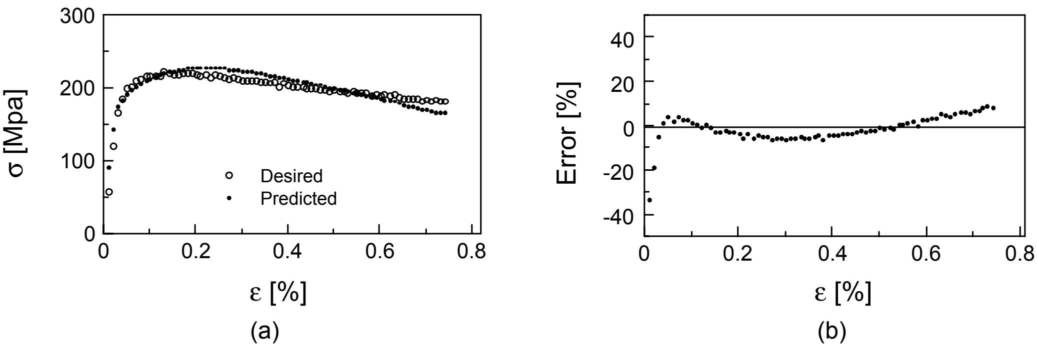

Fig. 4. 7-3-1 NN config. using input vectors {ε, $\dot{\varepsilon}$, T, ln(ε), ln($\dot{\varepsilon}$), 1/T, ε_p}. Test n. 5: Nimonic 115: (a) Desired and predicted flow stress vs. strain; (b) flow stress percent error vs. strain.

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