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Superplasticity in PbSn60: Experimental and neural network implementation

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Abstract

This paper proposes a new technique based on artificial neural network useful for the characterization of superplastic behaviour, in particular for PbSn60 alloy. A three-layer neural network with back propagation (BP) algorithm is employed to train the network. The network input parameters are: alloy grain size, strain and strain rate. Just one is the output: the flow stress. Experiments are performed to evaluate the behaviour of PbSn60 alloy, subject to uniaxial tensile test, when the cross speed is kept constant. The strain rate sensitivity value (m) has been estimated analyzing the slope of the $\log\sigma$–$\log\dot{\varepsilon}$ curve. It is shown that BP artificial neural network can predict the flow stress and, consequently, the m index during superplastic deformation with considerable efficiency and accuracy.

Keywords: Artificial neural network; Superplasticity; PbSn60 alloy

1. Introduction

Artificial neural network modelling is a relatively new technique. It consists in a "black-box" operational linking input to output data, using a particular set of dynamic systems. Since artificial neural network modelling is a nonlinear statistical technique, it can be useful to solve problems that could not be approached with conventional statistical methods.

In the past few years there has been increasing interest in neural network modelling in different fields of materials science [1–4]. In this paper the application of the artificial neural network in the forecast of the superplastic behaviour of PbSn60 alloy is proposed. A superplastic material exhibits great elongation ($200 < \varepsilon < 1.000\%$) prior to failure with low deformation resistance. These features are obtained with high strain rate sensitivity values

$$m = \frac{d\log(\sigma)}{d\log(\dot{\varepsilon})} > 0.5 \qquad (1)$$

Besides, it is established that a fine grain size is fundamental requirement for superplastic forming. There is an increasing interest in producing metals with very small grain size. This interest arises because a reduction in grain size leads to better mechanical properties at room temperature and, if the small grain size are stable at high temperature, where diffusion is reasonably rapid, is possible to achieve good formability and superplastic ductility. Furthermore, because the strain rate in superplasticity is proportional to $1/d^2$, where d is the material grain size, a reduction in grain size can increase the strain rate with optimum superplasticity. This possibility is important because any expansion of commercial superplastic forming is currently restricted by the relatively slow strain rates (about 10^{-3}–$10^{-2}\ \mathrm{s}^{-1}$) for the fabrication of each superplastic component [5–11].

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Except for grain size, during the superplastic deformation process there are many factors that influence the flow stress and the strain rate sensitivity (m) of the metal. The value of "m" is the most important characteristic of a superplastic material. There is a great number of reports in literature where various experimental methods to determine the value of m are described [6,12]. At the same time analysis shows that "m" value depends on a few factors: strain, strain rate, structure evolution, deformation mode and type of applied load. The effects of these factors on "m" and on flow stress are very complex and the relationships between the strain rate sensitivity index and these factors are non-linear: consequently, it is very difficult to describe the flow stress of a metal during superplastic deformation with a mathematical expression by the method of regression of experimental data.

In this paper, an artificial neural network is applied to establish a constitutive law and correlate the relationship between the microstructure and process parameters during superplastic deformation of PbSn60 alloy. During the training of the network, the process parameters and the grain size of superplastic deformation are considered as input variables and the flow stress is taken as output. A set of experiments is performed to evaluate the flow stress of PbSn60 alloy, subject to uniaxial tensile test at constant cross speed, varying the microstructural parameters.

The artificial neural network at first was developed using a set of experimental data for training and then another one to validate the neural model.

2. Materials and experimental procedure

The material used in the experimental procedure is a two phase PbSn60 alloy, in the form of extruded bars (thickness 3.6 mm). It consists lead (60 wt.%) and tin (40 wt.%).

In this work the choice of the PbSn60 alloy has been dictated by the opportunity to carry out the superplastic deformation process at room temperature. With the purpose to determine an optimal range of the microstructural requisites, some cycles of rolling and folding with different deformation steps have been performed on the alloy.

The first series of rolling reduces the thickness of the bars to around 0.3 mm (step 1). Four foils are overlapped and rolled again to reach a thickness of around 0.3 mm (step 2) (Fig. 1).

The foil has been subjected to four folding cycles. In the first one and in the fourth cycle (step 3 and 5) the PbSn60 alloy has been folded three times and subsequently rolled, in the second and in the third cycle (step 4 and 6) the material has been folded four times and rolled, to get one foil with a thickness of 0.3 mm (Fig. 2).

At the end of each step a few samples have been obtained for metallographic analysis with optical microscope and for tensile tests.

Observations with optical microscope and the image analyses have been performed in order to study the microstructural variations during the successive steps of rolling. For the mechanical characterization a set of samples have been submitted to tensile test. For every step the tests have been performed at different cross speed (0.016, 0.05, 0.083, 0.166, 0.216, 0.283, 0.333, 0.400, 0.533, 0.716, 0.966, 1.283, 1.733 and 2.333 mm/s). The results have been reported on log-log diagrams ($\log\sigma - \log\dot{\varepsilon}$), σ calculated at fixed deformation (10, 20, 30, 40, 50, 60, 70 and 80%) but evaluated at different strain rate ($= v/l$ in which v is the crosshead speed in mm/s and l is the length in mm of the sample). The value of m has been determined analyzing the slope of the log–log curve. In this paper, based on above experimental data, a three-layer feed-forward network with a back-propagation learning rule has been employed to investigate the constitutive relationship of PbSn60 alloy. The method used for this study has been the Levenberg–Marquardt algorithm, which can be regarded as a compromise between Gauss–Newton and Steepest–Descent, heavily favouring the former. Typically, the use of Levenberg–Marquardt leads to a reduction of orders of magnitude in the number of training iterations required if compared with back-propagation and is highly reliable [13,14]. In this paper the neural network models were designed and trained using the Matlab package.

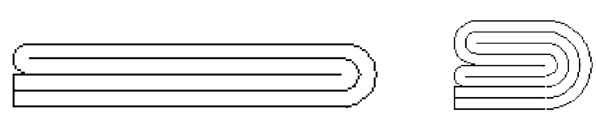

Fig. 2. The cycles of folding.

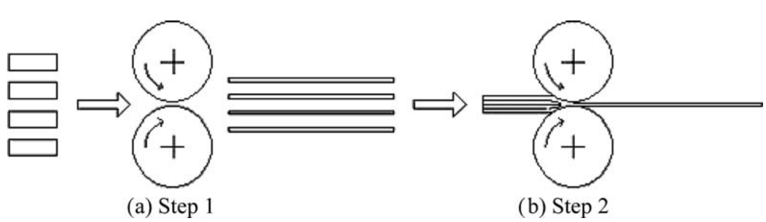

Fig. 1. The cycles of rolling.

The experimental results, related to the evolution of the flow stress as a function of the strain rate, have been organized for every step in the two sets of data (training and validation set) to use for the training and validation of the neural network. The parameters used for the elaboration of the neural network and the

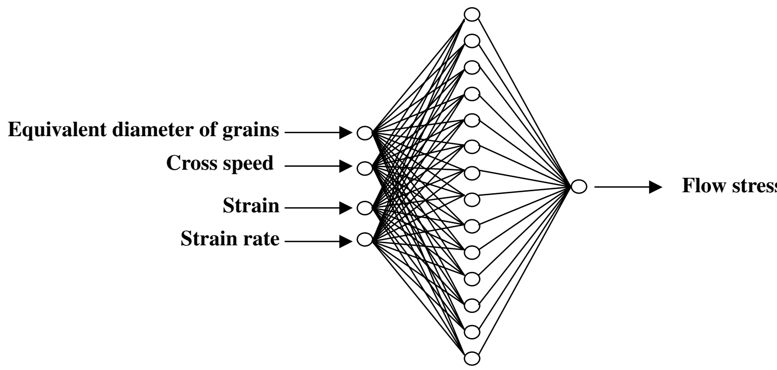

Fig. 3. Architecture of the neural network model.

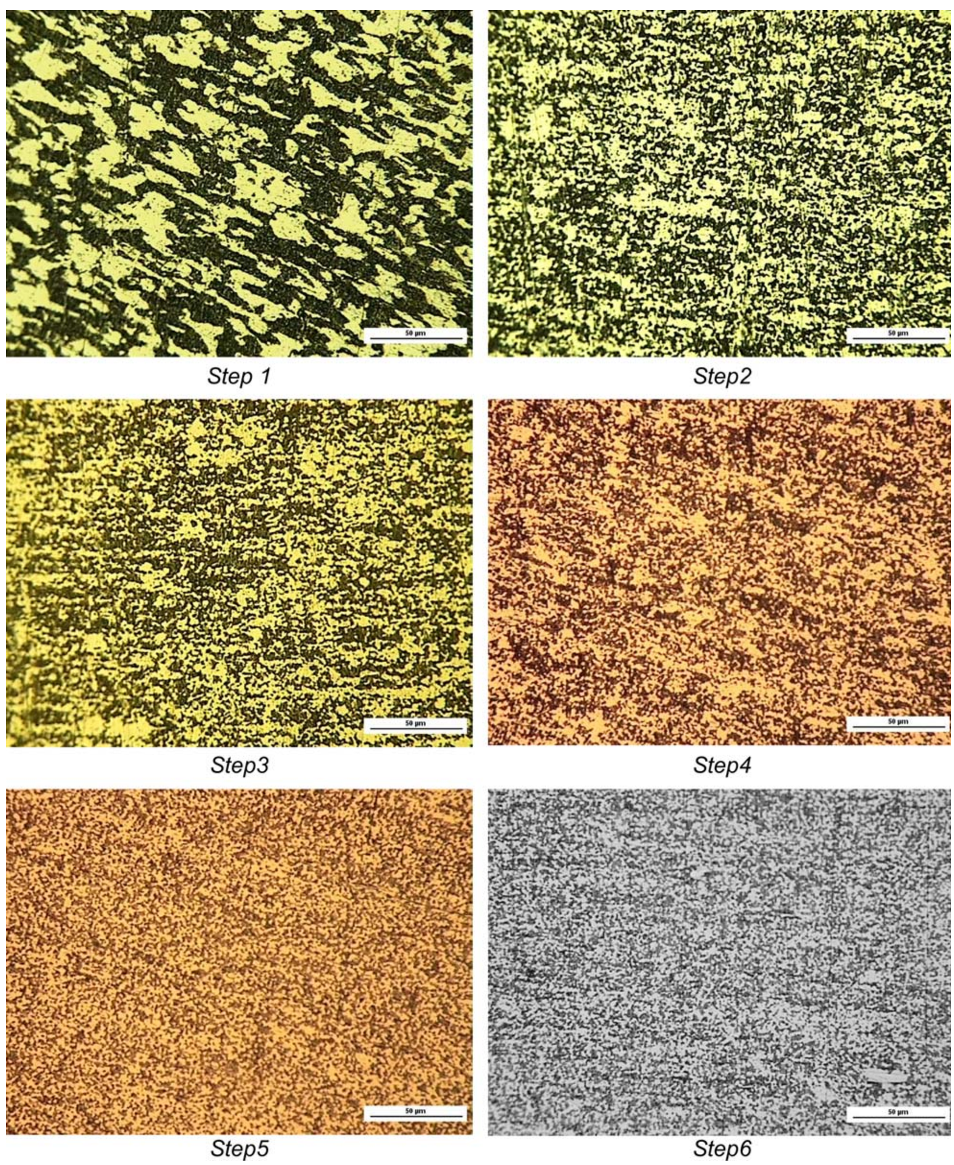

Fig. 4. The microstructures of the PbSn60 alloy after the different steps of deformation.

corresponding architecture (Fig. 3) are reported in the following:

No. of input neurons = 4,
No. of hidden neurons = 14,
No. of output neurons = 1.

Training set = 23 curves × 12 points.

Step 1; $\varepsilon = 10, 40, 50\%$;
Step 2; $\varepsilon = 10, 20, 60, 70\%$;
Step 3; $\varepsilon = 10, 40, 50, 80\%$;
Step 4; $\varepsilon = 20, 30, 50, 70\%$;
Step 5; $\varepsilon = 10, 60, 70, 80\%$;
Step 6; $\varepsilon = 10, 30, 40, 80\%$.

Validation set = 8 curves × 12 points.

Step 1; $\varepsilon = 20\%$;
Step 2; $\varepsilon = 40, 80\%$;
Step 3; $\varepsilon = 70\%$;
Step 4; $\varepsilon = 60\%$;
Step 5; $\varepsilon = 30\%$;
Step 6; $\varepsilon = 50, 70\%$.

Minimum error = 10^{-5}.
No. of epochs = 2000.

The neuron in exit is represented by the logarithm of the tension, plotted vs the logarithm of the strain rate (-3 to $0\ \mathrm{s}^{-1}$). All data should normalized and then submitted to the neural network so that they are confined between 0 and 1. Therefore, "m" value analogously has been determined analyzing the slope of the trend of the $\log\sigma$–$\log\dot{\varepsilon}$ curve.

Table 1
The equivalent diameters at successive steps of deformation

Step	1	2	3	4	5	6
d_{eq} (μm)	8.37	3.36	1.88	1.70	0.75	0.70

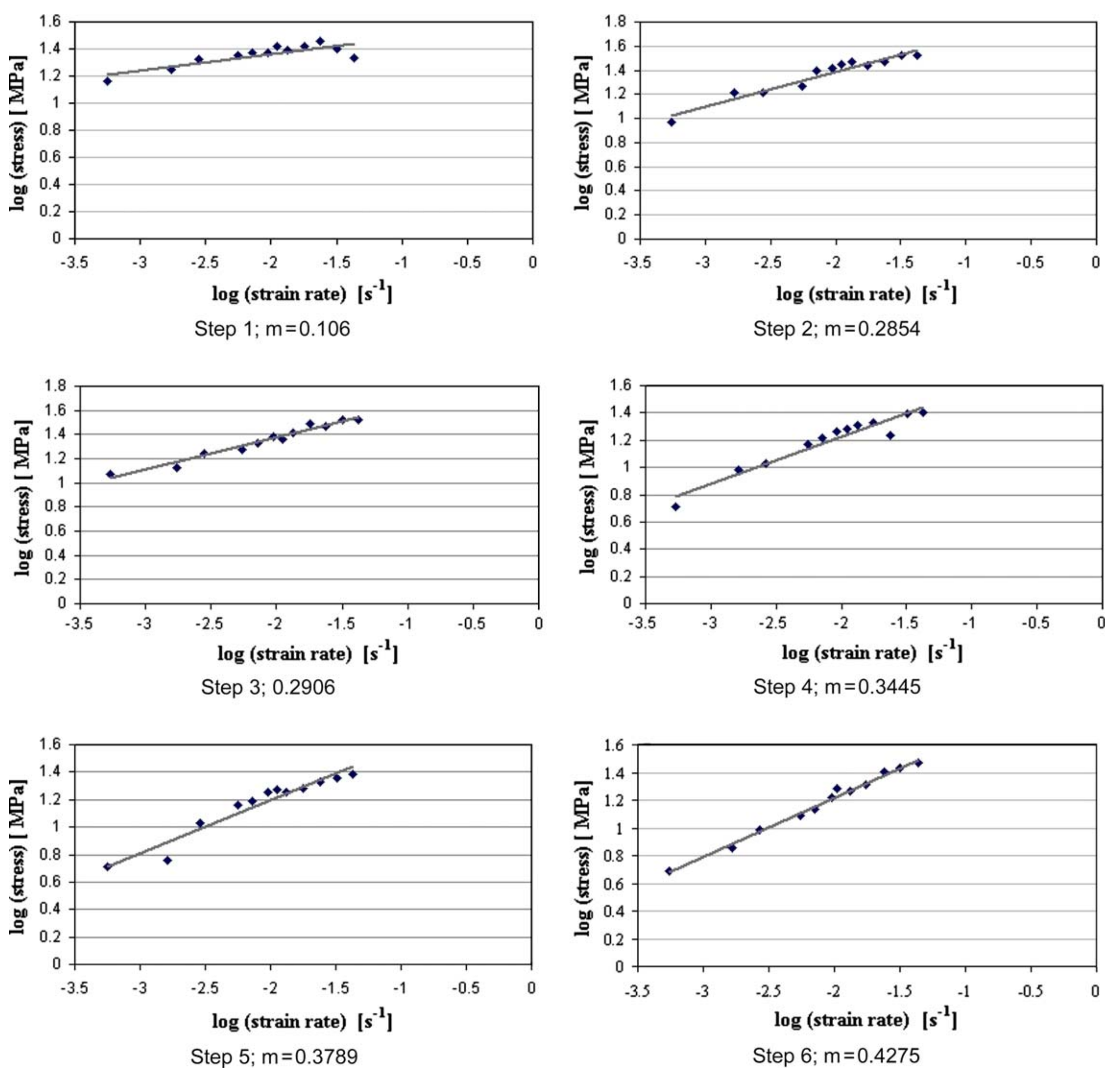

Fig. 5. $\log\sigma$–$\log\dot{\varepsilon}$ diagram.

3. Results and discussion

In Fig. 4 the microstructures of the samples obtained with the six following stages of folding and rolling are shown. For all the examined samples, through a technique of digital image analysis, the equivalent mean diameter of the grain has been calculated:

$$d_{eq} = \sqrt{\frac{4A}{\pi}} \tag{2}$$

where A is the area of the circle with the same area of the correspondent object.

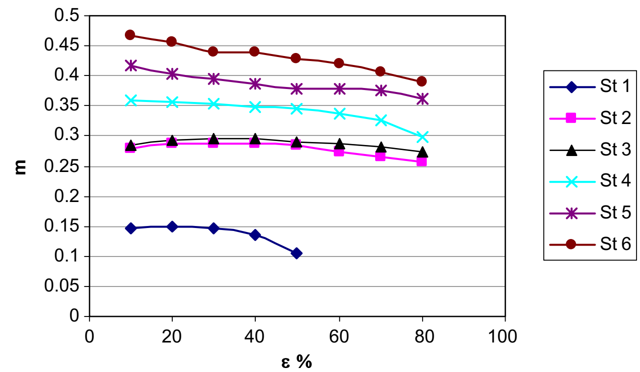

Fig. 6. Trend of "m" as a function of the strain for different steps.

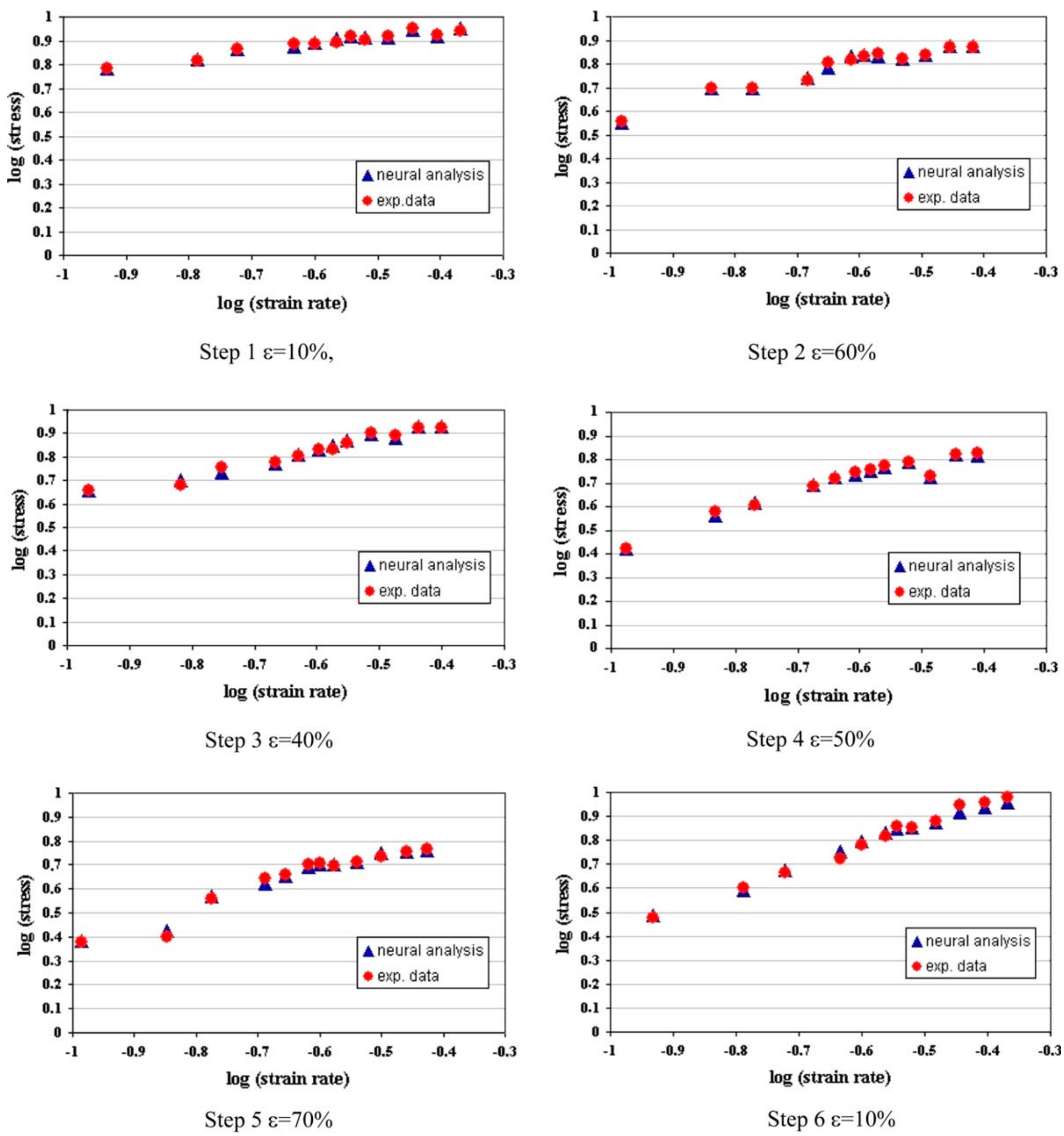

Fig. 7. Comparison among the trend of the $\log \sigma$ (MPa) in relation to $\log \dot{\varepsilon}$ (s^{-1}): neural analysis (red triangles) and the experimental data (blue points) in the training phase are overlapped. (For interpretation of the references in colour in this figure legend, the reader is referred to the web version of this article.)

In Table 1 the equivalent mean diameters are reported for the different steps measured on the micrographies of Fig. 4. Measurements have been repeated on 10 micrographies of the same sample.

The complete cycle of the grain refinement, based on the rolling and the folding at room temperature, has induced a considerable reduction of the grain size (Fig. 4). The gradual increase of the deformation rate influences the method of nucleation during recrystallization. It can be attributed to the different distribution of the dislocations inside the grains; in the rolled structure, in fact, the plastic deformation is generally heterogeneous and leads to the sites of deformation and dislocations cells. Besides, the irregular deformation produces a notable increase of potential sites of nucleation for the following recrystallization and therefore it conducts to a finer structure [15].

Fig. 4 shows that increasing deformation rate also involves a modification of the grain size and shape. In the first step of refinement, grains are elongated in the rolling direction; in the last three stages of deformation, grains show finer and equiaxed features. Small-equiaxed

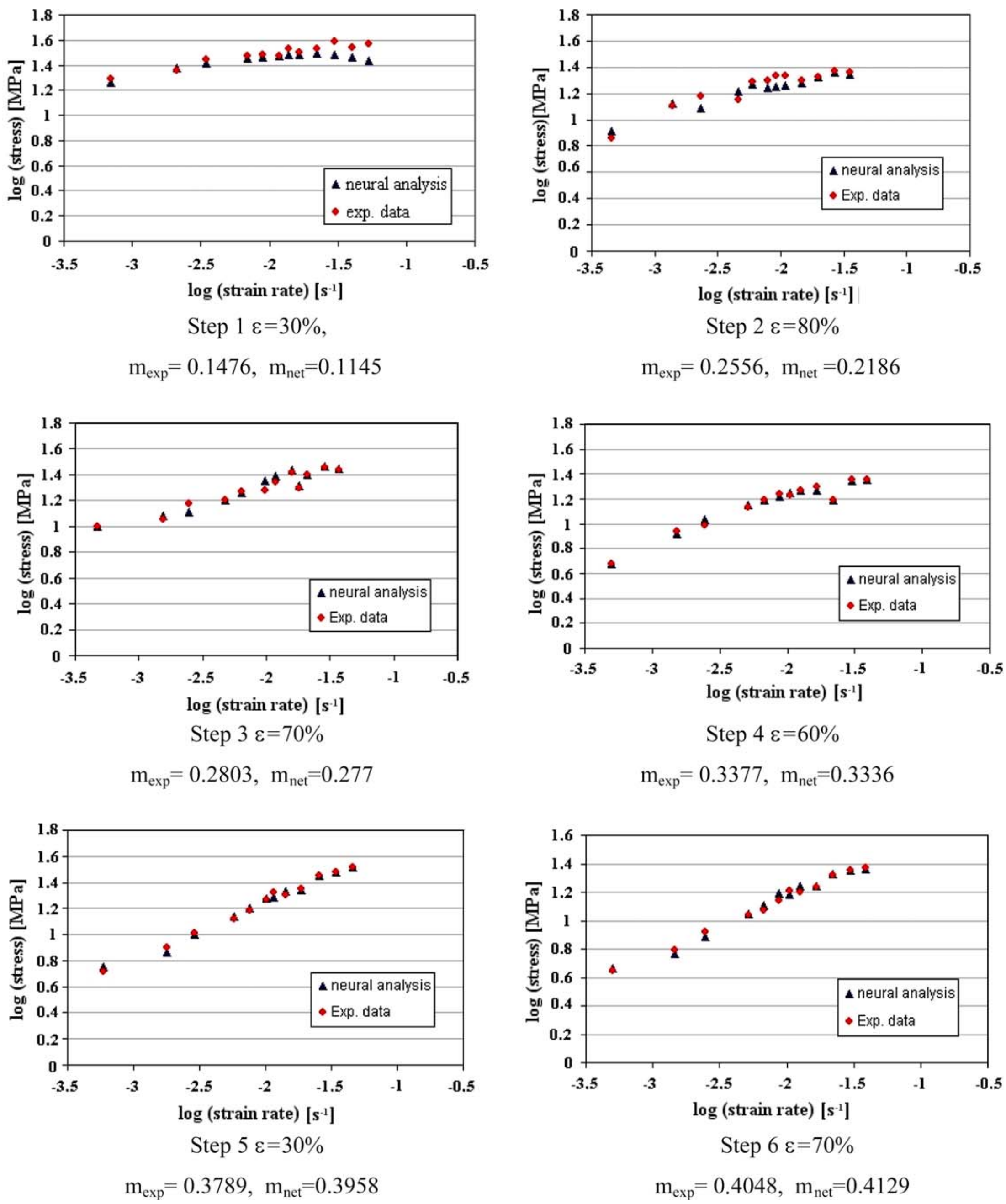

Fig. 8. Comparison among the trend of the $\log\sigma$ (MPa) as a function of $\log\dot{\varepsilon}$ (s^{-1}) for the neural analysis and the experimental data in the validation phase.

grains and biphasic structure are the main requirements for grain boundary sliding mechanism and allow superplastic flow. From tensile test data the flow stress has been calculated as a function of the strain rate for a fixed value of the strain. For every $\log\sigma - \log\dot{\varepsilon}$ curve the angular coefficient m has been calculated as the slope of the curve. Fig. 5 shows the $\log\sigma - \log\dot{\varepsilon}$ curve obtained with different grain size, at fixed strain ($\varepsilon = 50\%$) and the correspondent values of m.

In the first and second steps the coefficient m has been found lower than the limit of superplasticity, and the elongation to failure, for all the test conditions, has been lower than 200%.

For each grain size the evolution of the strain rate sensitivity value has been evaluated as a function of the strain. Fig. 6 shows that, for a fixed microstructure, the higher the strain applied the lower the "m" coefficient. The behaviour can be correlated to the state of hardening of the material and is function of the grains size and shape. According to these results for lower values of the grain size <1.88 μm (steps 3–6) the alloy exhibits superplastic behaviour under all the test conditions. The fine and equiaxed microstructure enhances grain boundary sliding and consequently the superplastic deformation also for higher values of the strain rate. For higher values of the grain size >1.88 μm (steps 1 and 2) low values of the "m" coefficient are found and consequently superplastic behaviour is observed in a small range of flow stress and strain rate. As a results in these microstructural conditions superplastic forming results economically disadvantageous.

The experimental results have been used to develop the artificial neural network. From a first analysis of the curves, in the training phase, it is observed that the neural network, implemented for the forecast of the superplastic behaviour of a PbSn60 alloy, reaches a good level of learning (Fig. 7).

The value of the "m" coefficient, in analogous way to experimental data, has been determined analyzing the slope of the curve $\log\sigma - \log\dot{\varepsilon}$, supplied by the artificial neural network in the validation phase. In Fig. 8 a comparison between the experimental trend $\log\sigma - \log\dot{\varepsilon}$ and those calculated by the neural network while validating is shown. In Table 2 the error committed by the neural analysis in the determination of the "m" value has been reported.

Table 2
The experimental and neural values of the "m" coefficient, calculated in different microstructural condition and strain during the validation phase

Step	ε (%)	m (experimental)	m (neural network)	Error (%)
1	30	0.1476	0.1145	3.31
2	80	0.2556	0.2186	3.7
3	70	0.2803	0.277	0.3
4	60	0.3377	0.3336	0.4
5	50	0.3789	0.3958	1.69
6	70	0.4048	0.4129	0.8

The percentage error is negligible if the equivalent grain diameter of the alloy is lower than 1.88 μm, while as the grain size increases the ability of generalization of the neural network (steps 1 and 2) is lower.

4. Conclusions

The artificial neural networks are a good forecast tool also in metallurgy to study non linear phenomenona. In the strain rate range in which the PbSn60 alloy shows superplastic behaviour the neural network is perfectly able to foresee the course of the flow stress in relation to the strain rate and consequently to evaluate with accuracy the value of "m". Besides, with the aid of the neural analysis is possible to determine quickly the transition of the plastic–superplastic behaviour. Particularly in the field of the superplasticity it is possible to evaluate the influence of the grain size, of the strain and of the strain rate, in the quantitative evaluation of the coefficient "m". Therefore, it is possible to forecast the superplastic behaviour, reducing time and cost of the experiments.

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