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Neural network implementation for the prediction of load curves of a flat head indenter on hot aluminum alloy

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Abstract

The indentation test performed by means of a flat-ended indenter is a valuable non-destructive method for assessment of metals at a local scale. Particularly, from the indentation curves it is possible to achieve several mechanical properties. The aim of this paper is the implementation of an artificial neural network for the prediction of the indentation load as a function of the penetration depth for an aluminium substrate. In particular, the neural network is addressed to the mechanical characterization of the bulk in function of temperature and indentation rate. The results obtained showed a high accuracy in curves prediction.

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Keywords: Artificial neural networks; Non-destructive tests; Curves prediction; Materials characterization

1. Introduction

Within the industrial manufacturing field, the ability of evaluate the mechanical feature of a given component is crucial. In particular, it is of great interest the opportunity to perform test that leaves the specimen intact. Several methodologies have been developed with this purpose and presented in the literature [1,2]. Among this methodologies, the indentation tests have been reported to be useful for the determination of several mechanical properties [3–7]. Recently, a new typology of indentation test for metallic materials has been developed, which is performed with a flat-ended indenter [8], and applied for the characterization of materials in several previous works [9–12]. The indentation test allows to identify load versus penetration depth trend defining an elastic stage and successively different plastic stages (Figure 1). In particular, it is possible to achieve a correlation between the yield stress metals and the load at the end of the first plastic stage, as reported in [13]. Anyway, the correlation between indentation curves load-penetration depth and yield stress was valuated only for a penetration rate of 0.1 mm/min.

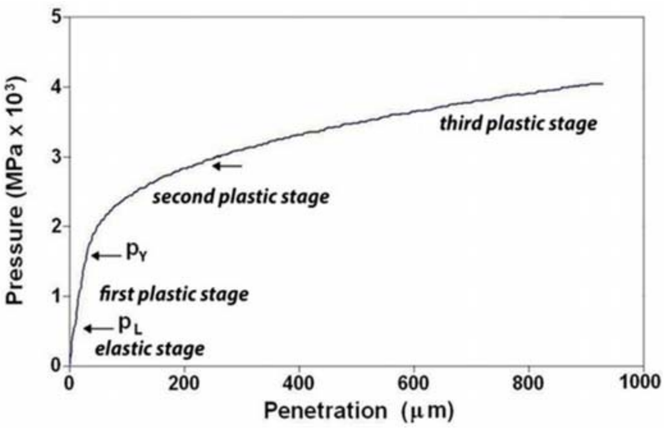

Fig.1 Example of indentation curve achieved by means of flat-ended tips [8].

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The need to evaluate the mechanical properties of material without destructive tests is an interesting requirement for different design aspects. In this context, Artificial Neural Networks (ANNs) are included, which are valuable tools for the prediction of complex and difficult to model phenomena. A neural network is a computational structure, consisting of a number of highly interconnected processing units called neurons [14–16]. The neurons sum weighted inputs applies a linear or nonlinear function to determine the output, then this output is passed to the following neurons, which are arranged in layers and are combined through excessive connectivity [17–19]. The process of training neural networks is the most challenging part of using the technique in general and is by far the most time consuming, both in terms of effort required to configure the process and computational complexity required to execute the process [19–21]. Neural networks are effective and efficient alternative to conventional methods, such as: numerical modelling methods, which could be highly computationally expensive; analytical methods, which could be difficult to obtain for newly achieved devices; and empirical modelling solutions, due to huge range and limited accuracy [22–24]. ANNs are information processing systems with their design inspired by studies of the ability of the human brain to learn from observations and to generalize by abstraction. In particular, ANNs learn from an empiric survey to give response when unknown examples are analysed. They have been widely accepted as a technology offering an alternative way to simulate complex and ill-defined problems. ANNs have been used in many applications, such as: control, robotics, pattern recognition, forecasting, power systems, manufacturing, optimization, signal processing, etc., and there are particularly useful in system modelling [25–32]. In particular, ANNs have already been used to predict the trend of the penetration load curves in a duplex steel, depending on the indentation conditions and the secondary phases involved in the microstructure. In this work, two feedforward neural networks have been developed to model the flat indentation test on Aluminium alloy 6082 T6 in order to predict the curves load penetration depth and the value of load relatively at the end of the first plastic stage. In a first phase, indentation tests were carried out at different temperatures and penetration rates. Subsequently, experimental data were used for the training and validation of the two artificial neural networks described.

2. Materials and methods

In order to characterize aluminium by means of indentation tests performed with a flat–ended indenter, samples of Al6082 T6 were cut in a cylindrical specimens of 40 mm diameter and 15 mm height. The characteristic of the aluminium alloy chosen for this work are briefly reported in Table 1.

Table 1 Al6082 mechanical properties.

Property	Value	Unit
Density	2.70	$g \cdot cm^{-3}$
Hardness	95	Vickers
Ultimate Tensile Strength	290	MPa
Yield Strength	250	MPa
Thermal conductivity	170	$W \cdot m^{-1} \cdot K^{-1}$

The indentation tests were performed exploiting a tungsten carbide flat head tip with a diameter of 1 mm. It was connected with the crosshead of a “MTS 50 Insight” tensile test machine, used to perform the indentation test, by means of a steel shaft. In order to perform tests at high temperature, the samples were placed in oven heated by means of electrical resistance, which dimensions were 250x250x200 mm. It was isolated from the environment by means of a layer of refractory material of 50 mm and the temperature was measured by means of a thermocouple placed on the sample surface. The upper side of the device had a rectangular opening of 40x40 mm to perform the test. The experimental setup is reported in Figure 2. To evaluate the load at the end of the linear portion of the load-penetration depth curves acquired, which is correlated to the material’s yield stress, a MATLAB model was developed. First step of the model was the fitting of the experimental point acquired during the indentation test to find the best approximating function. It was effectuated by means of a 9th grade polynomial equation. Once the function was find, the derivative was calculated. The model developed consider the midpoint of the linear section as the penetration depth value where the maximum value of the derivative is reached. As the middle of the linear behaviour was calculated, a linear fitting of the experimental point was performed considering growing range around the midpoint of the linear section. The penetration depth interval considered for the fitting was increased until an R^2 value of less than 0.999 was reached. The schematization of the model developed is reported in Figure 3.

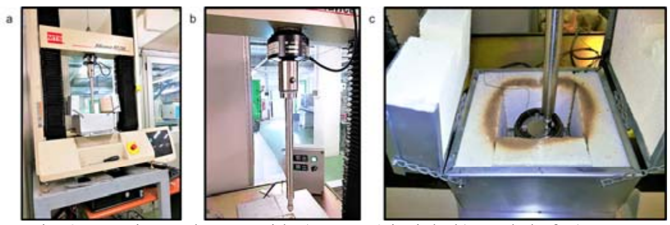

Fig. 2 Experimental setup with a) MTS50 insight b) steel shaft c) oven.

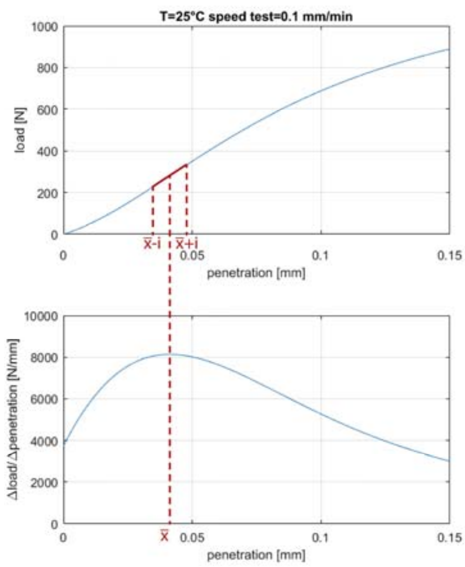

Fig. 3 Schematization of the model for the evaluation of the load at the end of the linear region.

For the Al6082 aluminium alloy characterization the variables considered were indentation rate and substrate temperature. In particular, 5 indentation speed and 3 temperatures were considered for the experimental plan designed, as reported in Table 2. For each condition three different tests were performed, up to a penetration depth of 0.3 mm.

Table 2 Variables considered for the Al6082 characterization.

Property	Value
Temperature	25-100-200 (°C)
Indentation rate	0.1-0.2-0.5-1.0-1.5 (mm/min)

The experimental data acquired were finally exploited for the development of two artificial neural networks. A first network, NET1, was aimed at the prediction of the load-penetration depth curves. The input variables considered are substrate temperature, indentation rate and penetration depth, considered as discrete intervals of 0.01 mm. Therefore, each curves give 30 input examples for the training. The output variable is the indentation load, which was plotted in function of the penetration depth. On 15 curves acquired, 12 were exploited for the network training while 3 for the validation. This means that the training was performed with 360 example the validation with 90 example. In particular, the curves exploited in the validation were obtained at 25, 100 and 200 °C with an indentation rate of 0.5 mm/min.

The ANNs structure which gave the best fit is reported in Figure 4. It features 3 hidden layers of 4 neurons each, an input layer composed of 3 neurons and an output layer with a single neuron. The transfer function connecting input and first hidden layer was the log-sigmoidal transfer function. The transfer function between the last hidden layer and the output layer was the purelin transfer function. The connection among the hidden layers were created with the tan-sigmoidal transfer function. The training algorithm set was the Scaled Conjugate Gradient.

A second artificial neural network, NET2, was developed for the prediction of the load at the end of the first plastic stage. The artificial neural network architecture designed counts two hidden layers respectively of 40 and 10 neurons for a 2:40:10:1 scheme, as depicted in Figure 5.

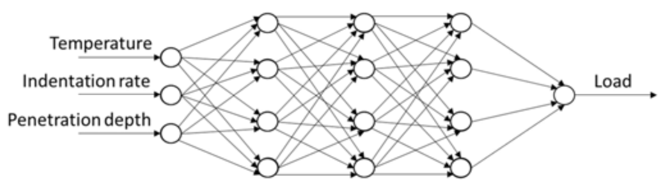

Fig. 4 NET1 structure.

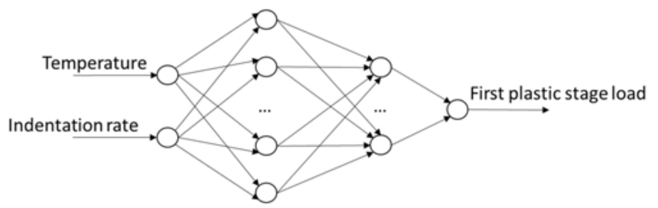

Fig. 5 NET2 structure.

The neurons of the input layer are representative of the two input variables while the output neurons represent the load at the end of the first plastic stage. The connection between the input and the first hidden layer was the log-sigmoidal function whereas the other connections were realized by means of a tan-sigmoidal transfer function.

The training was performed exploiting the Scaled Conjugate Gradient algorithm and 12 on 15 of the experimental data acquired.

3. Results and discussion

The experimental curves acquired are reported as follow in Figure 6 and 7. Anyway, for the sake of clarity, only a single curve for each condition was reported.

From the curves analysis reported in Figure 6, it is possible to notice a nonlinear stage in the very first part of the curves. This is due to an imperfect parallelism between tip surface and sample surface. The non-linear stage decreases with temperature increments since the bulk offers a reduced resistance to the indenter. As the contact between indenter and substrate is completely established, begins the linear stage of the curves until the second plastic stage, where the slope slightly decreases. Observing the curves, a trend with the indentation rate can be found. Indeed, indentation speed increments lead to the shift of the curves to the top. On the other hand, the temperature affects the results shifting the curves to the bottom as highlighted in Figure 7. The linear region of the curves end for minor load values for the whole indentation rates considered when the temperature is increased, as verified by the MATLAB's model implemented. The loads at the end of the first plastic stage evaluated for the different indentation condition are reported as follow in table 3. Furthermore, the load evaluated with the model described were plotted as a function of the test rate in an exponential fit, as depicted in Figure 8.

Analysing the value reported in Table3 it is evident the low standard deviation, which means that the method it is highly replicable. It is worth to note how the curves at different temperature shows similar trends. This means that the load evaluated with this method has the same sensitivity to the test rate at different temperature, differently from the result achieved by a tensile test.

On the base of the experimental results achieved, an artificial neural network was trained for the prediction of the load-penetration depth curves. The results achieved are reported in Figure 9, where the solid line represent the actual curve and the dotted line the predicted curve.

The network NET1 showed a great ability in curves prediction as the two curves can be superimposed. For a quantification of the network error, the percentage error evaluated at a fixed penetration depth. The overall curves were evaluated by means of the two norm vector. The results are reported in Figure 10.

Despite NET1 allows the prediction of the indentation curves with a great accuracy, an elevated error was committed in the early stage of the tests. This is due to the non-linear trend of the curve caused by a partial contact between tip and substrate. Anyway, the error rapidly decreases and after penetration depth of about 0.05 mm, approximatively where

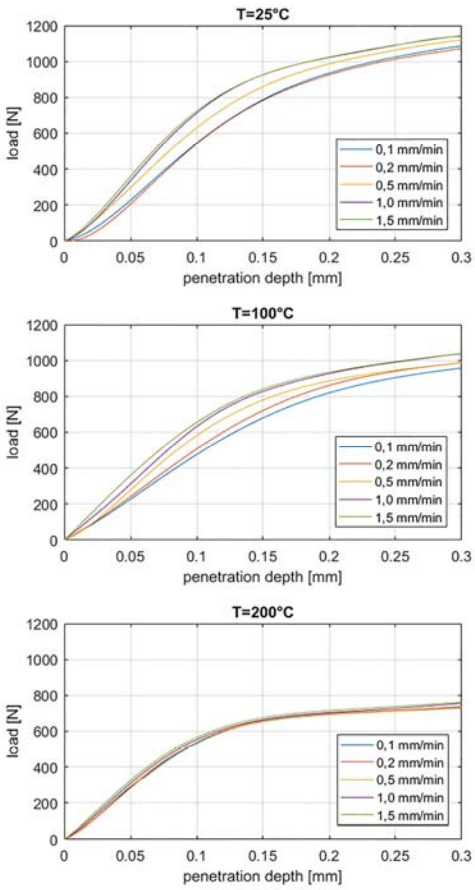

Fig. 6 Load-penetration depth curves in function of indentation rate for different substrate temperature.

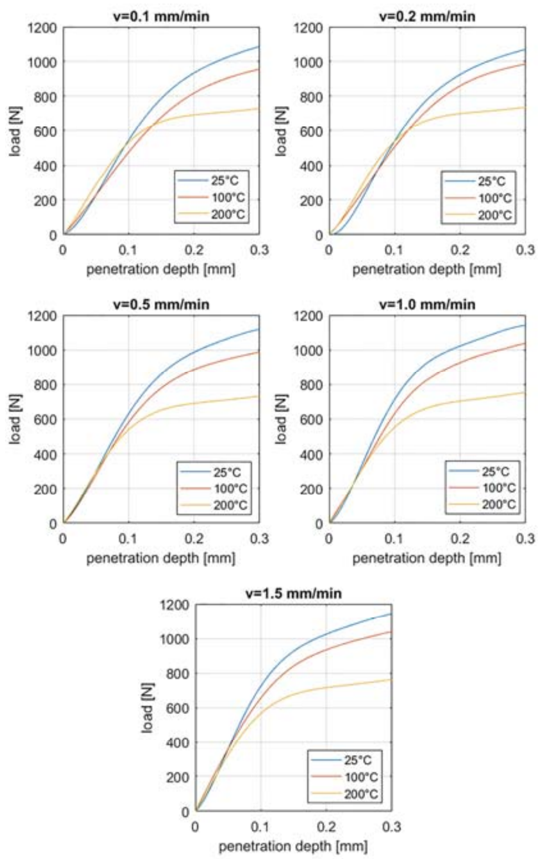

Fig. 7 Load-penetration depth curves in function of substrate temperature for different indentation rate.

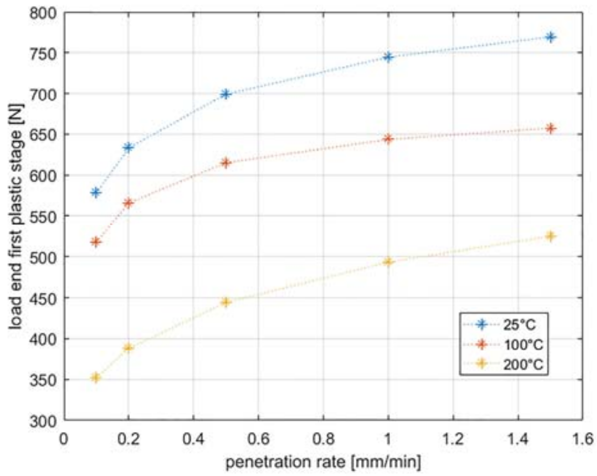

Fig. 8 Trend of the load at the end of the linear region as a function of penetration rate and temperature.

Table 3 load evaluated at the end of first plastic stage.

Temperature (°C)	Indentation rate (mm/min)	Load (N)	Standard deviation (N)
25	0.1	578.68	8.99
	0.2	632.17	15.67
	0.5	699.41	26.36
	1	742.52	18.16
	1.5	769.35	7.04
100	0.1	520.04	7.52
	0.2	561.09	9.92
	0.5	612.94	15.37
	1	643.52	21.67
	1.5	657.32	19.73
200	0.1	352.57	4.54
	0.2	386.61	8.69
	0.5	443.86	6.87
	1	495.84	27.84
	1.5	523.48	15.2

the linear stage begins, is below the 5%. The overall evaluation by means of the 2-norm vector highlights the ability of the network in predicting the indentation curves. As a matter of fact, there is a high similarity between the actual and the predicted curves with a percentage error of about 6% for the test performed at 25 and 100 °C and about 4% for the test performed at 200 °C. Anyway, these results are heavily affected by the initial stage of the curves where the network committed error up to 30%.

Finally, an artificial neural network was developed with the aim of predicting the value of the load of the first plastic stage under different condition (NET2). The results obtained are reported in table 4 in terms of percentage error.

Table 4 results achieved in the final load of the first plastic stage.

Validation example		Actual load (N)	Predicted load (N)	Error (%)
Temperature (°C)	Indentation rate (mm/min)			
25	0.5	699.41	727.30	3.99
100	0.5	612.94	598.35	2.38
200	0.5	443.86	431.85	2.70

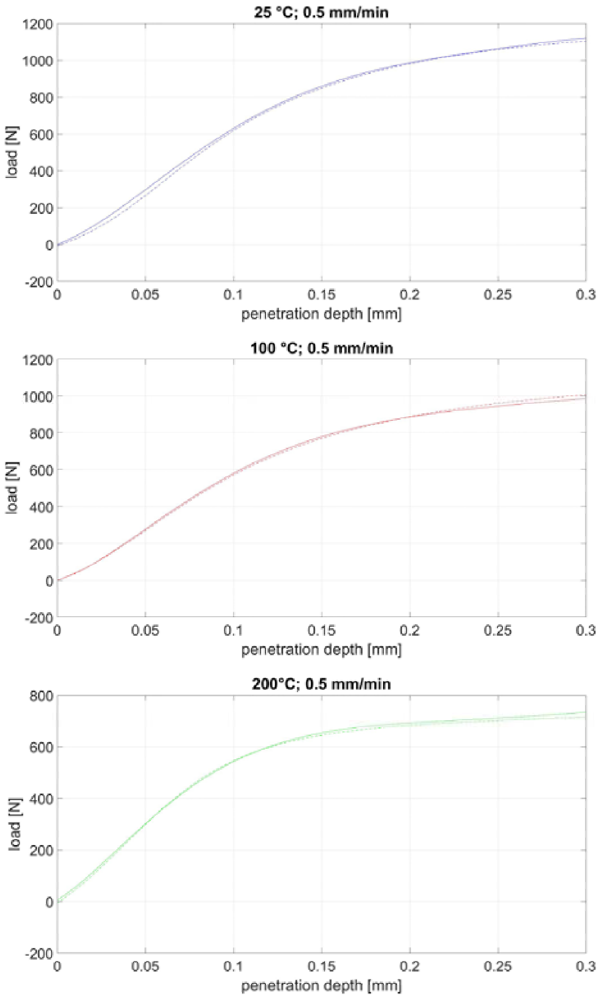

Fig. 9 Comparison between actual and predicted curve.

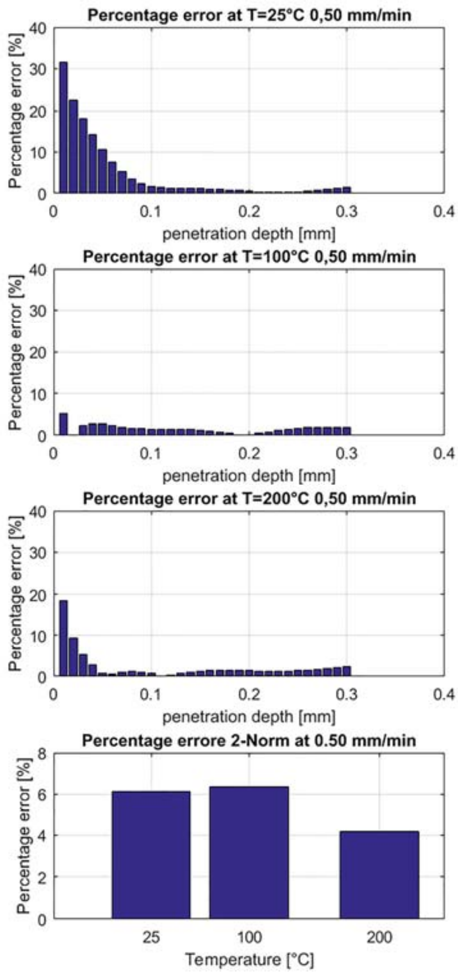

Fig. 10 Percentage error committed in the validation of NET1.

It can be noticed how the error committed in the evaluation of the load at the end of the first plastic stage is less than the error obtained in curve prediction, despite reduced example exploited for the training of this second network. Indeed, NET2 produces a hidden model that emulates the load-penetration rate curves. Being this model characterized by a monotonic and smooth trend it is possible to obtain accurate predictions, differently from NET1 which performance is affected by the initial non-linear trend.

Anyway, on the light of the results achieved, it is evident how it is possible to predict both the load at the end of the first plastic stage with an outstanding accuracy, as the mean error is equal to 3.02%, and the indentation curves.

4. Conclusion

The indentation tests performed by means of a flat indenter is a valuable method for the characterization of materials. The load value obtained at the end of the linear stage of indentation curves have been proved to be related with the result of a classic tensile test. With the present work, the analysis of the linear stage of a load-penetration depth curve was performed in different condition. As expected, the load of the first plastic stage decreases with temperature. On the opposite, it increases with test speed up to an asymptotic value function of the temperature.

From the trend of the load at the end of the linear stage in function of the indentation rate, it is evident how it features the same sensitivity to the test rate at different temperature. Furthermore, the evaluation of the load presents low standard deviation. This means that the method is highly replicable also at high temperature. Finally, the results were exploited for the training of two artificial neural networks aimed at predicting the load-penetration depth curves and the load at the end of the first plastic stage. The results obtained highlight a great accuracy with a very low mean error. In conclusion, ANNs may be a valuable method for the characterization of the mechanical performance of aluminium substrate.

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