INTRODUCTION

Material properties and the determination of material behavior is a subject of fundamental importance not only to scientific fields such as Physics and Chemistry but to many engineering disciplines as well. Particularly in manufacturing technology, knowledge of material properties such as mechanical, thermal but also behavior in electromagnetic fields or chemical environments is crucial. It concerns the development of manufacturing processes in order to select the proper process parameters for each material or to exploit material properties in a favorable way and perform these processes more efficiently.

Material behavior is often described by constitutive laws either theoretical or empirical. However, several efforts have been conducted to use artificial neural networks (ANN) as an alternative method for the prediction of material properties. Several notable works in this field have been presented in the past. Zhang et al. [1] used an artificial neural network model to predict the flow stress of a high alloyed austenitic stainless steel. The model was used in order to study the hot deformation behavior of this particular metal. Their data were derived from isothermal compression tests at the temperature range of 1000-1200 °C and at the strain rate range of 0.01-10 s⁻¹. The ANN model consisted of a three layer network with three inputs, namely strain, strain rate and temperature, nine hidden neurons and one output neuron, i.e. flow stress, and was trained using a set of 280 input/output data. This approach was able to model the data sufficiently as the model predicted the flow stress for an unknown data set of 60 samples with correlation coefficient equal to 0.997 and an absolute error of only 2.06%.

Rakhshkhorshid and Rastegari [2] employed ANN models to predict the flow curves in ferrite-cementite region during warm deformation. Their model was a feed-forward one with Bayesian regularization training algorithm and the data were derived from warm compression tests at the temperature range of 620-770 °C and strain rate range of 0.01-10 s⁻¹. In total 720 input/output data samples were used and the network consisted of three layers, with three input nodes, 40 hidden nodes and a single output node. They found that root mean square error (RMSE) values for the various phases of network training were at the range of 3.70-5.36 MPa, which indicated a high level of accuracy for the prediction of the network.

Senthilkumar et al. [3] investigated the application of constitutive and ANN models to predict the flow behavior of an Al/Mg based nanocomposite at high temperatures. They collected data at various strain rates in the range of 0.01-1.0 s⁻¹ and at various temperatures, namely 523, 623 and 723 K. The total number of 45
input/output samples was employed in a multilayer perceptron (MLP) neural network model trained with Levenberg-Marquardt algorithm. From the trial runs, the optimum network topology was 3-22-1 neurons for the input, hidden and output levels, respectively. The performance was assessed by means of mean relative error (MRE), RMSE, correlation coefficient and scatter index. It was found that the ANN model was superior to all constitutive models for all performance indexes.

Gupta et al. [4] in their study of flow stress during dynamic strain aging regime of 316 austenitic stainless steel, used an ANN model for the prediction of stress under various conditions. They conducted various tests at temperatures between 350 and 650 °C and strain rates between $10^{-4}$ and $10^{-2}$ s$^{-1}$. The 90% of the collected data, i.e. 498 values, was used for the training of the model whereas 10%, i.e. 55 values, was preserved for validation and test procedures; the number of hidden layer neurons was determined from a trial and error process as 15. Using this model, the correlation coefficient was found to be 0.998 for the training data and 0.995 for the testing data.

Sheikh-Ahmad and Twomey [5] created an ANN constitutive model for deformation of Al 7075-T6 under high strain rate. The data for the model were derived from Split Hopkinson pressure bar (SHPB) tests for three strain rates, ranging between 1300 and 3100 s$^{-1}$, and four temperature values, between 25 and 300 °C. It is noteworthy that they also included data from orthogonal machining test in order to extend their model capability to higher strain rates. For the neural network, a special stop training method was employed, namely 0.623e estimate method and the total training samples were 736. The neural network included three input nodes, 20 hidden nodes and a single output node. This model was shown to perform particularly well compared to Lee’s constitutive model.

Sabokpa et al. [6] modeled the flow behavior of an AZ81 magnesium alloy by means of an ANN model. They performed isothermal hot compression tests in a temperature range of 250-400 °C and strain rates of 0.0001-0.01 s$^{-1}$. A total of 308 input/output data samples were derived from these tests. The ANN model consisted of a three layer network with 15 hidden neurons. It was shown that this model outperformed an Arrhenius-type constitutive equation both in terms of correlation coefficient and error.

Apart from the aforementioned works which consider strain, strain rate and temperature as inputs, there exist some works in the literature concerning models in which more input variables are included to enhance the performance of the model. Kong et al. [7] employed an ANN model with six inputs, namely strain, strain rate, temperature, work-hardening rate, another two variables related to work-hardening rate and stress and Zener-Hollomon parameter. They conducted experiments at temperatures in the range of 900-1100 °C and strain rates in the range of 1-30 s$^{-1}$ and also included data from the Estrin-Mecking model. They concluded that the proposed integrated phenomenological and artificial neural network model with experimental data was superior to other models used in that study and could perform well even at conditions outside the range of experimental data.

Phaniraj and Lahiri [8] applied an ANN model for the prediction of flow stress in respect to the carbon content of steels. For their model they used previous experimental data for four types of steel, temperatures from 850-1100 °C and strain
rates from 0.1-40 s⁻¹. Their model had two hidden layers with a topology of 4-5-6-1, which was determined regarding root mean sum of squared deviation. They concluded that, compared to constitutive models, the ANN model was superior as they did not exceed 10% error in any case.

In the current work, artificial neural network models are developed with a view to predict the mechanical behavior of aluminum alloy at various strain rates and temperatures.

ARTIFICIAL NEURAL NETWORKS

Artificial neural networks constitute a well-established soft computing method, which can be employed for the modeling of various phenomena. This method uses sets of input and output data regarding a specific process which needs to be modeled and without any prior knowledge of the modeled process, can determine the correlation between input and output data with significant accuracy for many cases. Due to the relatively low computational cost compared to other modeling methods it is very commonly used in many engineering disciplines.

The function of artificial neural networks is based on the function of real biological neural networks. Input data are considered as input signals to the network and data is processed in a forward way to the output layer. For each internal or hidden layer node, the input signals are summed and processed using an activation function before the data passes to the next layer.

The connection between neurons of adjacent layers is modeled using a weight coefficient, which is a very important part of the network as the determination of this coefficient through a learning procedure is the goal of the network. The network is trained by minimizing the error between actual and desired output when fed with sets of input/output data. At the end of the procedure, the network can predict the known outputs with a high level of accuracy and should also be able to generalize, e.g. to predict the response to unknown data with a sufficient level of accuracy.

Usually, some quantities that can be employed to evaluate the performance of a neural network are correlation coefficient (R), mean squared error (MSE), mean absolute error (MAE) and mean percentage error (MPE). The calculation of the three last quantities is performed by the following formulas, respectively:

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (\hat{Y}_i - Y_i)^2 \quad (1)
\]

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} |\hat{Y}_i - Y_i| \quad (2)
\]

\[
MPE = \frac{100\%}{n} \sum_{i=1}^{n} \frac{Y_i - \hat{Y}_i}{Y_i} \quad (3)
\]

where \(\hat{Y}_i\) represents the predicted output, \(Y_i\) the actual values and \(n\) the number of observations.
METHODOLOGY

In this study, MLP neural networks are employed for the prediction of mechanical properties of aluminum 7017 alloys at various strain rates, ranging from 0.01 up to 1500 s\(^{-1}\), and temperatures from 25 up to 300 °C. The ANN MLP approach involves the use of a model with three input neurons, regarding strain, strain rate and temperature respectively, a single hidden layer and a single output neuron representing the flow stress. All developed networks employ the same activation functions and the training algorithm is Levenberg-Marquardt with early stopping technique to abort the process when validation error is not improving after a certain number of epochs. The performance is assessed in terms of MSE during train and test and correlation coefficient \(R\) as well. The input/output data are derived by the experimental work conducted in [9]. Before using the data for the network, they are processed by special software so as to determine the pairs of strain and stress for each case.

The total size of input/output data pairs is 314 samples, which are considered sufficient for the correct representation of the experimental data. For this type of neural network, it is derived from the aforementioned literature than a single hidden layer is sufficient. However, the size of hidden layer is determined by the approach described in [1], in which the number of neurons is approximated by the following formula:

\[
n = \sqrt{N_{inp} + N_{out} + \alpha} \quad (4)
\]

where \(N_{inp}\) is the number of input neurons, \(N_{out}\) is the number of output neurons and \(\alpha\) is a number between 0 and 10.

The exact number of hidden neurons will be determined by a trial and error process. The input/output data are also properly normalized in the range of 0-1, in order to ensure that the relative magnitude of these values will not lead to incorrect correlation prediction between input and output parameters.

RESULTS AND DISCUSSION

Firstly, the results from the developed ANN model are presented. After determining the number of hidden neurons with a trial and error process within the suggested limits, already mentioned in the Methodology section, the network is developed and results are obtained.

In Fig. 1, the MSE during test, in respect to hidden neurons number is graphically displayed. According to the aforementioned graph the best performing network is the one with 10 hidden neurons. The ANN model was trained for 101 epochs, with an MSE train of 0.000142, MSE test of 2\( \times 10^{-4}\) and correlation coefficient \(R\) of 0.99837 and 0.99886 for train and test, respectively. The computational cost for the development of this model was rather low, about 1 second.

Although these metrics indicate that a significantly good fit of the experimental data was attained using the ANN model, the evaluation of proposed model is further
conducted using two other metrics, namely MAE and MPE, which were presented previously and are essential for a more global assessment. Thus, each of the predicted curves is compared to the experimental one, i.e. 16 in total, and RMSE, MAE, MPE as well as $R^2$ are calculated for each compared pair of curves individually to determine in detail the accuracy of the proposed mode in each case.

![MSE test in respect to the number of hidden layer neurons](image)

**Fig.1**
MSE test in respect to the number of hidden layer neurons

The comparison between predicted and experimentally derived curves is also presented for the case of $T = 25 \, ^\circ C$ and $T = 100 \, ^\circ C$ in Fig. 2 (a) and (b) respectively. In Table 1, the results for each different temperature value are displayed, for 4 cases of strain rate for each temperature value, concerning the minimum and maximum value of each quantity. From the results of Table 1, it can be seen that RMSE values for all cases vary from 2.7 to 10 in all cases except for the cases at $100 \, ^\circ C$ with average value of RMSE around 7. This indicates that the stress values are predicted with a maximum deviation of 14 MPa and an average deviation of 7 MPa. The values of the correlation coefficient are very close to 1 in every case, indicating a good fit, but it should be noted that this quantity cannot always provide a clear picture of the deviation between experimental and predicted data.

MAE and MPE, however, can provide a more direct measure of accuracy in these cases and it can be seen that the results almost in every case are below 10%, something that is generally acceptable and so the results using the ANN model can be successfully employed for the prediction of 7017 aluminum alloy properties for various conditions.
Results concerning stress-strain relationship at: (a) T = 25 °C and (b) T = 100 °C

The fact that results for T = 100 °C and 200 °C exhibit larger errors than the other temperatures are due to the more irregular nature of the curves in these cases, indicating that a special treatment should be applied, perhaps representation with
more data points or use of a different kind of neural network that can provide even
more accurate prediction of material properties.

Table 1
ANN model results evaluation

<table>
<thead>
<tr>
<th>Temperature (°C)</th>
<th>RMSE</th>
<th>R</th>
<th>MAE (%)</th>
<th>MPE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>4.177-5.210</td>
<td>0.9948-0.9984</td>
<td>0.1192-0.2661</td>
<td>2.2942-3.9087</td>
</tr>
<tr>
<td>100</td>
<td>10.579-14.077</td>
<td>0.9936-0.9963</td>
<td>0.4904-1.15069</td>
<td>7.1400-9.4449</td>
</tr>
<tr>
<td>200</td>
<td>6.488-9.317</td>
<td>0.9919-0.9941</td>
<td>0.0314-1.0962</td>
<td>5.2420-7.5688</td>
</tr>
<tr>
<td>300</td>
<td>2.738-3.639</td>
<td>0.9943-0.9960</td>
<td>0.0147-0.2630</td>
<td>2.1812-3.0379</td>
</tr>
</tbody>
</table>

CONCLUSIONS

In this paper a neural networks model for the prediction of mechanical
properties of Al 7017 was developed. From this work several useful conclusions
were able to be drawn. It was shown that this model is particularly capable to be
employed for the prediction of material properties with a sufficient level of
accuracy. Furthermore, it is significant that it requires no previous knowledge of
material behavior or guessing of the type of correlation and it can be implemented
with a low computational cost.

The error and level of fitness varied among the different cases of stress-strain
curves, particularly at cases where the stress-strain curve exhibits some non-smooth
areas, but RMSE and correlation coefficient values were found to be within
acceptable level. Additionally, MAE and MPE did not exceed 10% in the majority
of cases with average values around 1 and 5% respectively.

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