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# Flow curve prediction of ZAM100 magnesium alloy sheets using artificial neural network-based models

Mohamad El Mehtedi[a], Archimede Forcellese[a], Luciano Greco[a], Massimiliano Pieralisi[a], Michela Simoncini[b,*]

[a]Università Politecnica delle Marche, Via Brecce Bianche, Ancona 60100, Italy
[b]Università degli Studi eCampus, Via Isimabrdi 10, Novedrate (Como) 22060, Italy

* Corresponding author. Tel.: +39-071-220-4798; fax: +39-071-220-4801. E-mail address: michela.simoncini@uniecampus.it

**Abstract**

A multivariable empirical model, based on an artificial neural network (ANN), was developed to predict flow curves of ZAM100 magnesium alloy sheets as a function of process parameters in hot forming conditions. Tensile tests were performed in a wide range of temperature and strain rate to collect the dataset used in the training and testing stages of the network. The generalization ability of the model was tested using both the leave-one-out cross-validation method and flow curves not belonging to the training set. The excellent fitting between experimental and predicted curves was proven the very good predictive capability of the model.


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*Keywords:* Magnesium alloy; Flow curve; Artificial neural network

## 1. Introduction

The current legislation on emissions into the atmosphere forces the transport industry, such as automotive and aerospace, to adopt solutions aimed at reducing the vehicle weight. Such aim can be pursued using lightweight materials. To this purpose, magnesium alloys have shown high potential for lightweight structural parts owing to their high specific strength [1, 2]. Unfortunately, such alloys cannot be cold formed due to their hexagonal close-packed crystal structure. The attitude of magnesium alloys to be subjected plastic deformation strongly increases with temperature owing to the activation of additional slip planes, such as prismatic and pyramidal. In previous works [3-6], the authors investigated AZ31 Mg alloy and showed that the attitude to be formed without failure increases and flow stress decreases with rising deformation temperature. Recently, similar studies in hot forming condition concerned the innovative ZAM100 magnesium alloy [7]. It was observed that, for a given temperature and strain rate, ZAM100 exhibits flow stress values lower than those of AZ31 alloy. Such different behavior, attributed to the lower content of alloying elements of ZAM100 with respect to AZ31, is very attractive because allows to perform hot forming processes with reduced working loads.

In designing hot forming processes, the knowledge of the relationship among flow stress and strain, strain rate, temperature and microstructure is very useful, even though the large number of experiments required can be very expensive and time consuming [8]. For such reasons, a model able to predict the flow curve as a function of the process parameters is required. Among the different approaches used, the analytical one can be very accurate even if modelling of the complex relationships taking place between the input and output parameters can be difficult [9]. An approach that allows to overcome such difficulty is based on the empirical non-analytical models. To this purpose, the artificial neural networks (ANN), since are able to solve a problem by learning

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rather than by a specific programming based on well defined rules, can be very useful [10-13]. The ANNs were widely applied in several fields of manufacturing processes [14-21]. Many researchers also applied ANN to predict the flow curves both in a single step [10, 11, 16, 22, 23] and in multistep deformation [22, 23] on several materials; however, no work on ZAM100 magnesium alloys can be found in the available literature.

In this framework, the present paper aims at modelling the equivalent stress - equivalent strain curves of ZAM100 magnesium alloy sheets, obtained by tensile tests performed at different temperatures and strain rates. In particular, an artificial neural network-based model was built in order to predict the flow stress as a function of strain, strain rate and temperature. The model was validated by comparing the experimental and predicted flow curves.

## 2. Material, experiments and neural network modelling

### *2.1 Material*

The material investigated was ZAM100 magnesium alloy, supplied in form of 3.1 mm thick sheet, produced by hot extrusion. It is an advanced alloy, with low content of alloying elements (0.86 Zn, 0.84 Mn, 0.62 Al, 0.1 Ca, 0.07 Sr), characterized by higher hot formability as compared to the traditional magnesium alloys.

The extruded sheets were hot rolled at 320°C, using a two-high mill stand, in order to obtain the desired thickness equal to 2.1 mm. Two passes, each of them carried out with a height reduction equal to 0.4 mm, were followed by the final one performed with a height reduction of 0.2 mm. The sheets were water quenched after hot rolling. [7]

### *2.2 Experimental procedures*

The equivalent stress (σ) – equivalent strain (ε) curves were obtained by means of uniaxial tensile tests carried out in extended ranges of temperature and strain rate (Table 1). Such tests allowed to collect the dataset used in training the artificial neural network and in testing the generalization capability of the trained ANN. Samples were obtained by water jet machining with the tensile axis parallel to the hot rolling direction. The gauge width and length of samples were equal to 12 and 23 mm, respectively. A servo-hydraulic testing machine, equipped with a resistance furnace, was used to tension samples until failure. For each temperature and strain rate condition, at least three samples were tension tested.

### *2.3 The ANN-based model*

A model based on an artificial neural network was developed in order to predict the flow curves as a function of the process parameters. To this purpose, a multi-layer feed forward ANN was built, trained and validated by means of the MATLAB® software. The back-propagation training algorithm was applied to adjust the weights of connections to minimize the error between the predicted and desired output [10].

Table 1. Experimental conditions of tensile tests carried out on ZAM100 Mg alloy

| | | $\dot{\varepsilon}$ [s$^{-1}$] | | | | |
|---|---|---|---|---|---|---|
| | | $1\cdot10^{-3}$ | $5\cdot10^{-3}$ | $1\cdot10^{-2}$ | $5\cdot10^{-2}$ | $1\cdot10^{-1}$ |
| **T [°C]** | 300 | X | | X | | X |
| | 325 | | | | O | |
| | 350 | X | | X | | X |
| | 375 | | O | | | |
| | 400 | X | | X | | X |

X: used in training the ANN
O: used in testing the ANN

On the basis of previous studies [7], the flow curves of ZAM100 were modelled using a six-input network. The input parameters were: i) equivalent strain ($\varepsilon$), ii) equivalent strain rate ($\dot{\varepsilon}$), iii) instantaneous value of temperature ($T$), iv) equivalent strain as logarithmic function ($ln\varepsilon$), v) equivalent strain rate as logarithmic function ($\ln\dot{\varepsilon}$) and vi) temperature as inverse function ($1/T$). The network output was the equivalent stress ($\sigma$). Fig. 1 shows the network architecture consisting of an input layer, two hidden layers, with six hidden neurons each, and an output layer. The training parameters, defined using a trial-and-error procedure with the experimental dataset reported in Table 1, are summarized in Table 2.

The ANN was tested at various stages of training on a validation dataset using the early stopping method [24] in order to avoid the overfitting. Although such method leads to an increase in the computational requirements of the learning process, it provides higher levels of generalization.

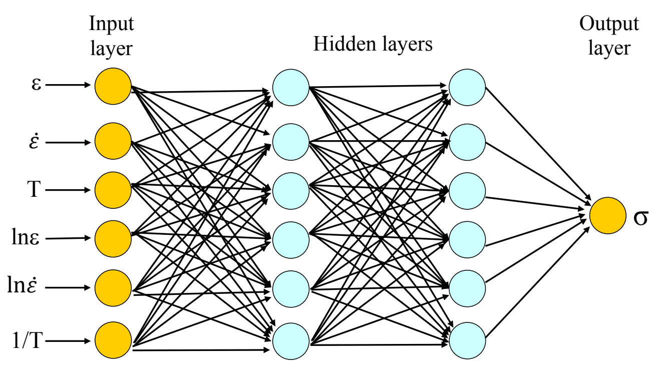


Fig. 1 Architecture of the proposed ANN-based model

Table 2 Training parameters of the ANN developed to predict the flow curves of ZAM100 magnesium alloy

| Network parameter | Content |
|---|---|
| Network type | Feed-forward back propagation |
| Training function | Levenberg - Marquardt |
| Adaption learning function | Gradient descent with momentum weight and bias learning function |
| Transfer functions for hidden layers | Tangential sigmoid |
| Transfer functions for output layer | Linear |
| Performance function | MSE |
| Training epoch | 300 |
| Goal | 0.0001 |

The generalization capability of the ANN-based model in predicting the flow curves was tested using a two-step procedure: in the former, the leave-one-out cross-validation (LOO-CV) method was applied [25], using the dataset marked with the "X" symbol in Table 1, whilst in the latter, the σ-ε curves not included in the training set, obtained under the process conditions marked with the "O" symbol, were predicted.

The predictive capability was quantified by means of the absolute relative error (ARE) and average the absolute relative error (AARE) defined according to the following equations:

$$ARE_i = \frac{|\sigma_{exp_i} - \sigma_{pred_i}|}{\sigma_{exp_i}} \cdot 100 \quad (1)$$

$$AARE = \frac{1}{N}\sum_{i=1}^{N} ARE_i \quad (2)$$

where $\sigma_{exp}$ and $\sigma_{pred}$ are the experimental and predicted equivalent stresses, respectively, and N is the total number of data of each flow curve.

The correlation coefficient (R) was also taken into account in order to evaluate the ANN response in a form of linear regression analysis between the ANN output (predictions) and the corresponding targets (experimental data).

## 3. Results

### 3.1 Experimental flow curves

Typical equivalent stress vs. equivalent strain curves of ZAM100 magnesium alloy sheets, obtained by means of tension tests carried out at different temperatures and strain rates, are shown in Fig.s 2 and 3. The σ value increases with ε until reaching a peak value; then, the flow stress decreases with increasing strain until sample failure. The strain effect on flow stress is strongest at the lowest temperature and highest strain rate investigated (300°C – 0.1 $s^{-1}$). It becomes ever less marked as temperature increases and strain rate decreases; the weakest effect is obtained at the highest temperature and lowest strain rate (400°C – 0.001 $s^{-1}$). Finally, the flow stress at 400°C is almost independent of strain due to the restoration mechanisms operating during deformation [7].

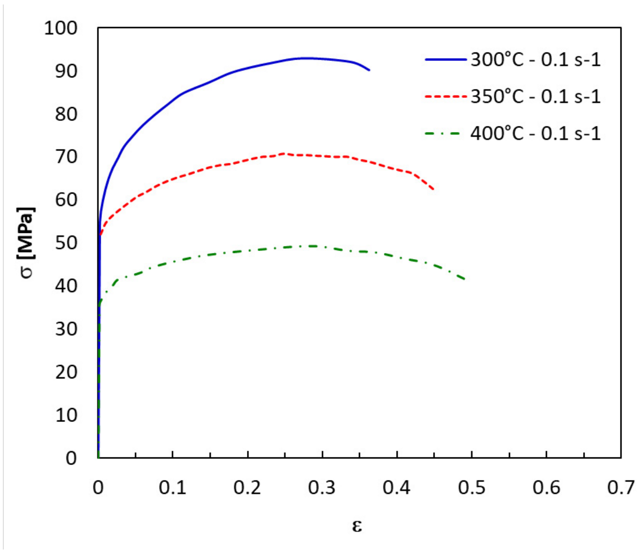


Fig. 2. Effect of temperature on the equivalent stress-equivalent strain curves ($\dot{\varepsilon} = 0.1\ s^{-1}$)

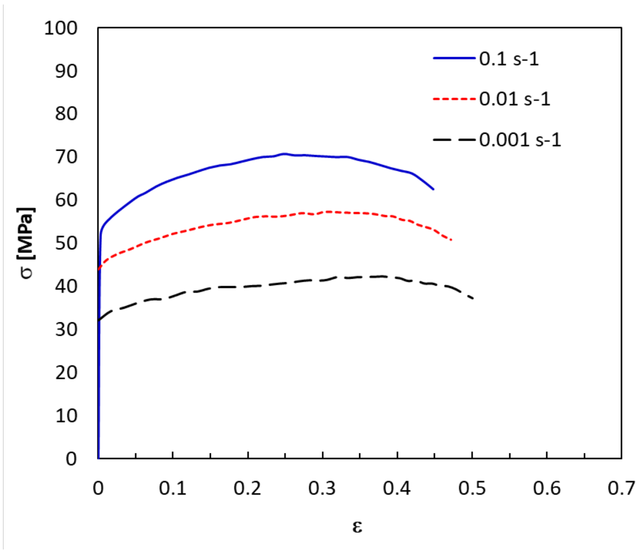


Fig. 3. Effect of strain rate on the equivalent stress-equivalent strain curves (T=350°C)

### *3.2 Predictive capability of the ANN-based model*

The flow curves of ZAM100 were predicted by means of the ANN-based model developed according to the architecture shown in Fig. 1 and training parameters reported in Table 2. In the first step of the procedure used for testing the generalization capability of the network, the leave-one-out cross-validation methodology was used. To this purpose, Fig. 4 shows the comparison between typical experimental and predicted flow curves. It appears that, for a given strain rate and temperature, the ANN-based model is able to predict both curve shape and stress values with absolute relative errors very low; more in detail, the model captures both the strain hardening effect occurring at the highest strain rate and lowest temperature and the softening one taking place at the lowest strain rate and highest temperature investigated. It is worth noting that such result was obtained without a priori knowledge of the complex microstructural mechanisms occurring during hot deformation of ZAM100 Mg alloy. The average absolute relative errors obtained in the different process conditions using the LOO-CV methodology, summarized in Table 3, are indicative of the excellent predictive capability of the ANN in modelling flow curves.

In the second step of the procedure, the ability of ANN-based model in capturing the effect of deformation parameters on flow curves was evaluated by comparing the experimental curves obtained under process conditions not investigated in the training data set (Table 1) with the predicted ones (Fig. 5). The very low values of the ARE and AARE prove the ability of the neural network to capture the influence of strain, strain rate and temperature on equivalent stress. Furthermore, by plotting the experimental values of the equivalent stress vs. the predicted ones (Fig. 6), it can be seen that the correlation coefficients (R) are equal to 0.994 as T = 325°C and $\dot{\varepsilon}$ = 0.05 $s^{-1}$, and 0.996, as T = 375°C and $\dot{\varepsilon}$ = 0.005 $s^{-1}$. These results confirm the excellent generalization capability of the ANN-based model.

The influence of strain rate and temperature is also shown in Fig. 7, in which the experimental and predicted peak stress values ($\sigma_p$) are compared. Consistently with the previous results, the $\sigma_p$ values predicted by ANN are almost coincident with the experimental ones. Furthermore, the peak stress values predicted at 325°C – 0.05 $s^{-1}$ and 375°C – 0.005 $s^{-1}$ are in excellent agreement with the trend resulting by the analysis of the experimental data.

Table 3. Average absolute relative error as a function of temperature and strain rate in the prediction of the σ-ε curves using the LOO-CV method

| **AARE [%]** | | $\dot{\varepsilon}$ [$s^{-1}$] | | |
|---|---|---|---|---|
| | | $1\cdot10^{-3}$ | $1\cdot10^{-2}$ | $1\cdot10^{-1}$ |
| **T [°C]** | 300 | 0.55 | 0.38 | 0.28 |
| | 350 | 0.70 | 0.66 | 0.38 |
| | 400 | 0.62 | 0.56 | 0.51 |

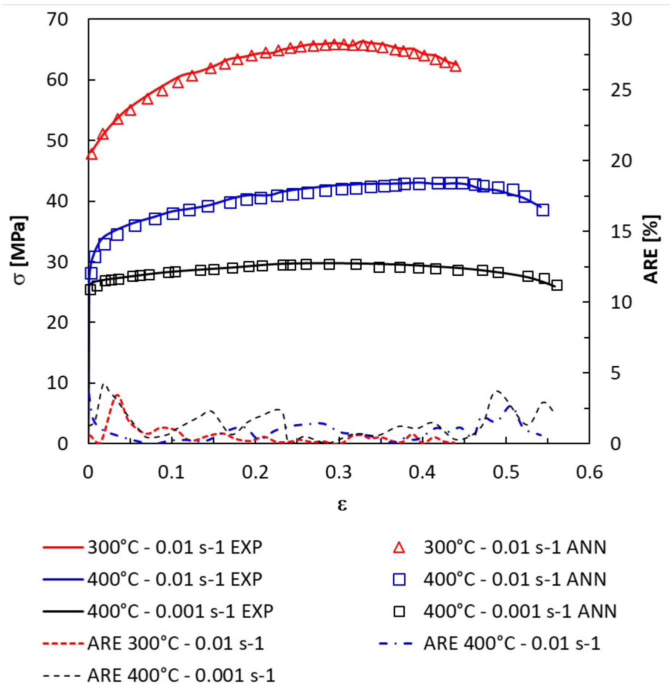


Fig. 4. Comparison between typical experimental and predicted flow curves, at different temperatures and strain rates, using the LOO-CV methodology, and absolute relative error

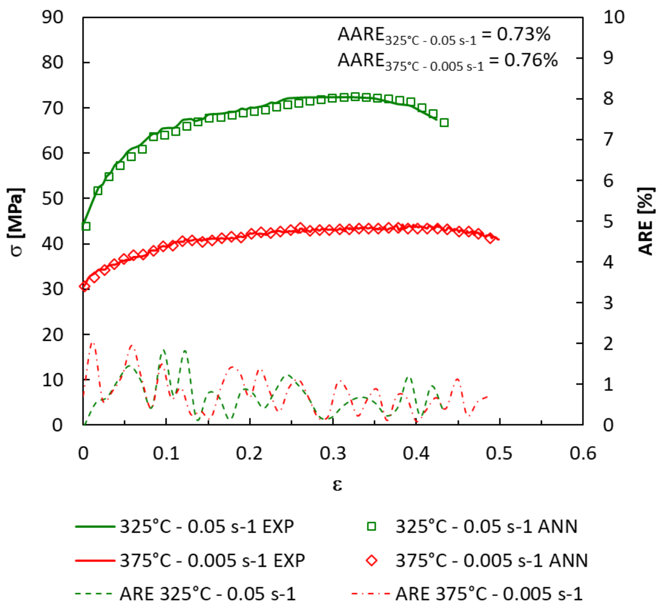


Fig. 5. Comparison between the predicted and experimental flow curves in temperature and strain rate conditions not included in the training dataset

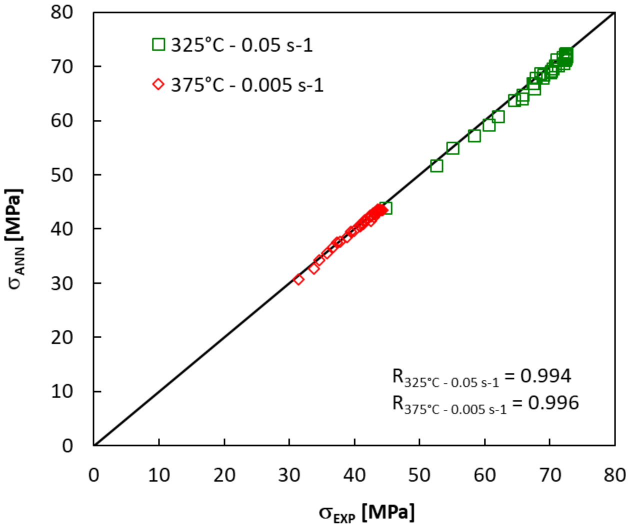


Fig. 6. Linear correlation plot between predicted and experimental equivalent stress in temperature and strain rate conditions not included in the training dataset

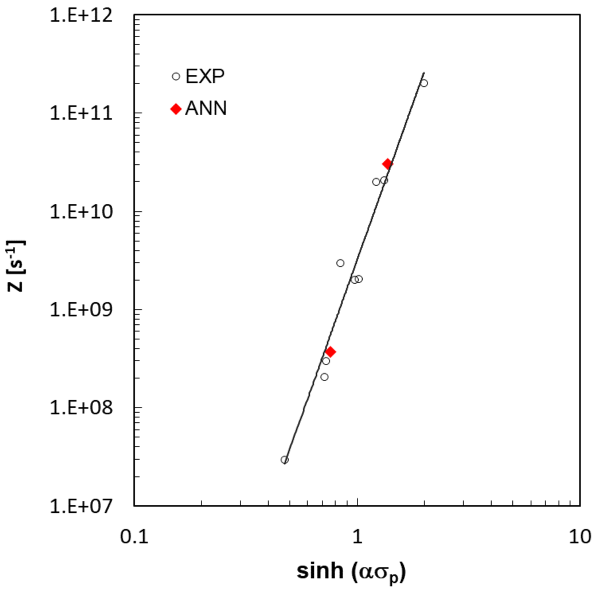


Fig. 8. Relationship between the Zener-Hollomon parameter and peak stress according to the Garofalo's equation ($\alpha$=0.0155 MPa$^{-1}$; Q=135 KJ/mol [7])

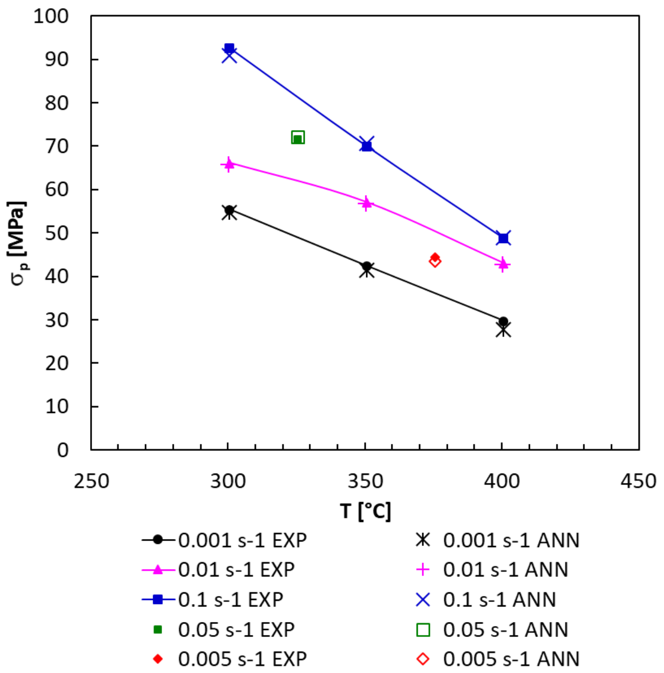


Fig. 7. Temperature dependence of the peak stress at different strain rates

Fig. 8 shows the relationship between the Zener-Hollomon parameter ($Z=\dot{\varepsilon}\cdot\exp(Q/RT)$) and peak flow stress according to the Garofalo's equation [26]:

$$\dot{\varepsilon} = A\left(sinh(\alpha\sigma_p)\right)^n exp(-Q/RT) \quad (3)$$

where n is the stress exponent, Q is the activation energy for high-temperature deformation, R is the gas constant, T is the absolute temperature, A and $\alpha$ are material parameters. It appears that the experimental data provided by the tension tests carried out under the strain rate and temperature conditions used in the training stage of ANN and marked with the "X" symbol in Table 1 quite closely align on a straight line; furthermore, the predicted $\sigma_p$ values, according to the process conditions used in testing the ANN and marked with the "O" symbol in Table 1, follow the same trend.

## 4. Conclusions

The flow curves of ZAM100 magnesium alloy sheets, under hot forming condition, were predicted by means of an artificial neural network. The input variables were instantaneous value of temperature, equivalent strain, equivalent strain rate, temperature as inverse function, equivalent strain as logarithmic function and equivalent strain rate as logarithmic function, while the network output was the equivalent stress. The capability of the ANN-based models in predicting the flow curves was evaluated using a two-step procedure based on both the leave-one-out cross-validation methodology on the utilization of process conditions not included in the training set. The absolute relative error, average absolute relative error and the correlation coefficient were measured to evaluate the generalization capability of the model. The main results can be summarized as follows:

- the ANN captures the influence of strain, strain rate and temperature on both flow curve shape and stress values, without a priori knowledge of the complex microstructural mechanisms occurring during hot deformation of ZAM100 Mg alloy;

- the low values of the absolute relative error and average absolute relative error, and the high correlation coefficients have confirmed the excellent generalisation capability of the artificial neural network;
- the predicted peak flow stress values follow the Garofalo's equation obtained by analyzing the experimental ones;
- the robustness of the ANN allows its effective utilization as a prediction tool to study the non-linear phenomena taking place during hot deformation.

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