Flow stresses of the AISI A2 tool steel

Krivulje tečenja za AISI A2 orodno jeklo

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Abstract: The hot deformation behaviour of the AISI A2 tool steel was examined with hot compression tests carried out in the Gleeble 1500D thermomechanical simulator in wide range of temperatures (900-1200 °C), of strain rates (0.001-10 s^{-1}) and of true strains (0-0.7). Due to the increased demands for the accuracy in predicting various parameters for the needs of optimization of hot forming technologies, it is nowadays reasonable to employ artificial intelligence for this purpose. Thus the obtained experimental database of flow stresses (curves) was used for such predictions with the CAE NN (Conditional Average Estimator Neural Network). Regardless of the scarcity of databases for strain rates (experimental data only for each decade) the mentioned approach enables to predict the flow stresses also for their intermediate states. The activation energy for the entire examined temperature range was calculated. The obtained value was compared with the reference data that had been acquired from the analysis of the hot torsion experiment.

Izvleček: Termomehanski simulator Gleeble 1500D je bil uporabljen za študij toplega preoblikovanja AISI A2 orodnega jekla. Stiskalni preizkusi v vročem so bili izvedeni v deformacijskem območju 0-0,7, temperaturnem območju 900-1200 °C in hitrostih deformacije 0,001-10 s^{-1}. Zaradi povečanih zahtev po natančnosti napovedovanja krivulj tečenja za današnje potrebe optimiranja tehnologij toplega preoblikovanja, je za te namene dandanes običajna uporaba nevronskih mrež. V našem primeru smo uporabili CAE nevronske mreže s katerimi smo lahko napovedovali krivulje tečenja tudi za vmesna (nemerjena) stanja tako za temperature kot tudi hitrosti deformacije. Izračunana je bila tudi aktivacijska energija za celotno temperaturno območje in primerjana z dobljeno vrednostjo na osnovi torzijskih preizkusov.

Key words: A2 tool steel, hot compression, flow stress, CAE neural network, hyperbolic sine function
Ključne besede: A2 orodno jeklo, vroče stiskanje, krivulje tečenja, CAE nevronske mreže, funkcija sinus hiperbolikus

INTRODUCTION

During the hot deformation many factors (Figure 1) influence the flow stresses of metal. The effects of these factors are very complex and the relationship between the flow stresses and the mentioned factors is a non-linear one, and spatially disordered[1-4]. The flow stresses during the hot metal forming cannot be in all cases accurately described with phenomenological or empirical mathematical models resulting from experiments. The accuracy is still unsatisfactory and it ranges from 2 to 60 %[5-10]. Hodgson and Kong[11-12] report that the accuracy needed for the prediction of flow stresses should be within 5 % for an efficient optimization of hot rolling technologies. Physically-based models have been improved quite a lot, but they are still limited more or less to rather pure metals and are not yet used in industrial applications[13], thus the development of constitutive equations from a purely empirical basis to a more physical-basis remains an important long term scientific objective. In spite of constantly new constitutive models for describing flow stress, there has not been any substantial improvement in accuracy as far as prediction is concerned. In recent time researchers began to use BP neural networks (BP NN) as an efficient predictive tool for flow stress predictions[3-4]. In this study we intentionally deal with the so-called CAE NN (Conditional Average Estimator Neural Network) which is, according to the author's opinion and experience, easier for use.

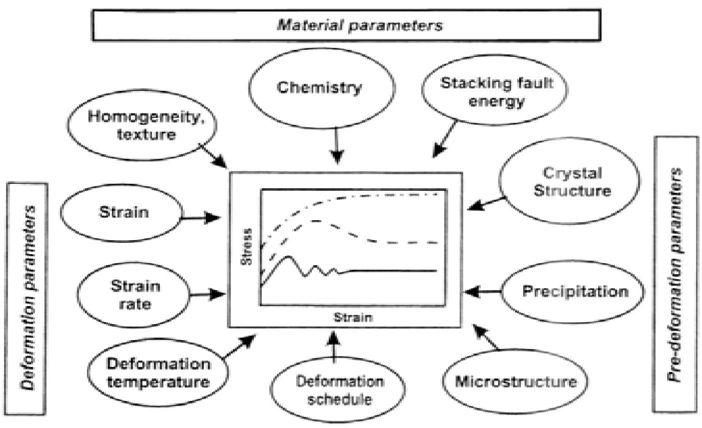

Figure 1. Parameters influencing hot flow stress curves[2]
Slika 1. Parametri, ki vplivajo na tople krivulje tečenja[2]

AISI A2 tool steel is conventionally hot forged (or hot rolled) after casting into ingots, and after the intermediate reheating the hot rolling process is continued to obtain the required dimensions. Increase of the productivity is oriented towards the hot forming of ingots with higher initial dimensions (cross sections and lengths) and toward the rolling to smaller dimensions (even below ϕ = 18mm); and for that an optimal determination of rolled billet cross-section reductions (roll pass design) with the regard to the loading capacities of the rolling mill itself, to the strength characteristics of the rolls, to the appropriate microstructures, etc is needed to be achieved. In the available references, the characterization of the working properties of the AISI A2 tool steel (generally applied for cold-working) refers to the hot torsion tests[14-15], while there are no available data on the hot compression tests.

In this paper hot compression tests were carried out in the Gleeble 1500D thermomechanical simulator to obtain experimental flow stress curves for the AISI A2 tool steel in a wide range of temperatures and strain rates. The flow stress curves were predicted also for intermediate states of influential parameters (strain rates, temperatures and strain) using CAE neural networks, for both, constant and non-constant smoothness parameters. The peak stresses were predicted with the hyperbolic sine function, and the constitutive equation constants were determined.

EXPERIMENTAL PROCEDURE

Specimens and material

The chemical composition of the AISI A2 tool steel is given in Table 1. Cylindrical specimens of the Rastegew type with dimensions ϕ = 8 mm x 12 mm were cut from the rod with cross section of ϕ = 90 mm which had been previously forged from a round (circular) ingot of ϕ = 400 mm x 1000 mm. The initial microstructure of the specimens is given in Figure 2.

Table 1. Chemical composition of the AISI A2 tool steel (wt %)
Tabela 1. Kemična sestava za AISI orodno jeklo (wt %)

C	Si	Mn	P	S	Cr	Mo	V
1.01	0.30	0.55	0.02	0.02	5.20	1.40	0.20

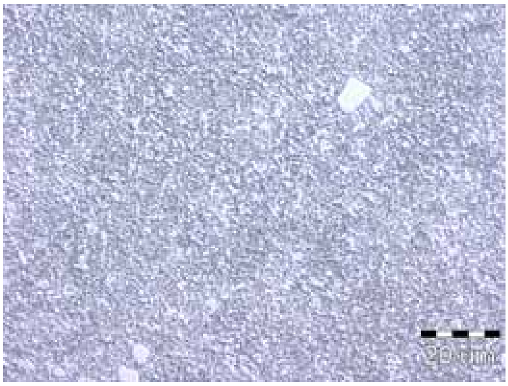

Figure 2. Initial microstructure of the applied tool steel (AISI A2), (soft annealed microstructure - spheroidal pearlite and carbides)
Slika 2. Začetna mikrostruktura orodnega jekla (AISI A2), (mehko žarjena, kroglasti perlit in karbidi)

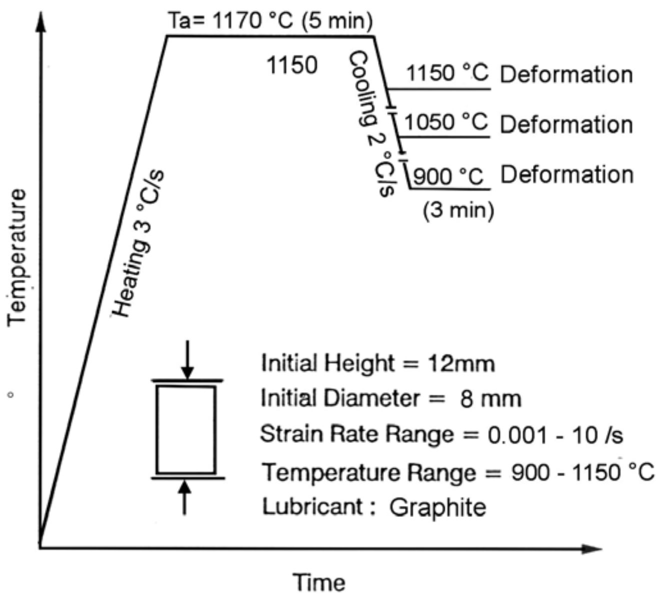

Figure 3. Schematic representation of the time-temperature relationship for the tested cylindrical specimens
Slika 3. Shematski prikaz časovnega poteka temperature vzorca med preizkusom

Procedure and testing conditions

A computer controlled Gleeble 1500 servo-hydraulic machine was used for compression tests. In order to reduce the friction between the cylindrical specimen and the tool, and to avoid sticking, graphite lubricant was used.

The testing conditions for the hot compression tests of cylindrical specimens are given in Table 2. Testing was performed at seven temperatures in the temperature range of 900 to 1150 °C (Figure 3), and with five different strain rates (0.001, 0.01, 0.1, 1, 10 s^{-1}). The heating rate was 3 °C/s, soaking (austenitizing) time 5 min at 1170 °C, followed by cooling at a rate of 2 °C/s down to the deformation temperature; with a further soaking time of 3 min.

It should be stressed here that hot compression at higher temperatures (1200 ºC) was not reasonable due to incipient melting; the grain boundary decohesion resulted macro-cracks on the deformed specimens (Figure 4). Figures 5 a-d show the stress-strain relations at different temperatures, between 900 and 1150 °C, with 50 °C intervals, and for five different strain rates, i.e. for 0.001 - 10 s^{-1}, respectively.

The flow stress curves have shapes typical for dynamic recovery (and recrystallization at lower strain rates), while the values of flow stresses are slightly higher in comparison with the results of flow stress curves that were obtained from the hot torsion tests (Imbert et al.[15-16]). They made tests only at four temperatures and with three strain rates.

Table 2. Values of the main parameters of the test
Tabela 2. Vrednosti glavnih testnih parametrov

Tool steel	Ta	Temp. range	Strain rate
AISI A2	1170 °C	900 -1150 °C	0.001- 10 s^{-1}

Ta .... *Temperature of austenitizing*

Figure 4. Appearance of macro-cracks on the compressed specimen, T = 1200 ºC, strain rate = 1 s^{-1}
Slika 4. Pojav razpok na površini deformiranega vzorca, T = 1200 ºC, deformacijska stopnja = 1 s^{-1}

APPLICATION OF A CAE NEURAL NETWORK FOR PREDICTION OF HOT FLOW STRESS CURVES

Derived equations

The problem analyzed in this paper is how to estimate the flow stress curves as a function of known parameters (data), i.e. temperature, strain, and strain rate. The first and the second set of variables will be called the output and the input variables, respectively.

Our aim is to demonstrate the potential applicability of the proposed method. In order to determine unknown output variables from the known input variables, a database containing sufficient number of well-distributed and reliable empirical data is needed. The database should include both, the measured values of output variables and the corresponding input variables. One particular observation that is included in the database can be described by a model vector. The input and output variables correspond to the components of this vector. For example, if the corresponding measured stress at the temperature T = 950 °C, strain 0.3 and strain rate 5 s^{-1}, is 350 MPa, then the model vector is defined as *{950, 0.3, 5; 350}*. The data base consists of a finite set of model vectors. A scheme of the structure of the CAE neural network is presented in references[16-17].

According to the CAE method, each of the output variables, corresponding to the vector under consideration (i.e. a vector with known input variables and output variables to be predicted), can be estimated by the expressions[18-22]:

$$\hat{r}_k = \sum_{n=1}^{N} C_n \cdot r_{nk} \qquad (1)$$

where

$$C_n = \frac{c_n}{\sum_{j=1}^{N} c_j} \qquad (2)$$

and

$$c_n = \exp\left[\frac{-\sum_{i=1}^{L}\left(p_i - p_{ni}\right)^2}{2w^2}\right] \qquad (3)$$

Here, $\hat{r}_k$ is the estimated (predicted) k-th output variable (e.g. *stress*), r_{nk} is the same output variable corresponding to the n-th vector in the database, N is the number of vectors in the database, p_{ni} is the i-th input variable of the n-th vector in the database (e.g. temperature, strain, strain rate), p_i is the i-th input variable corresponding to the vector under consideration, and L is the number of input variables.

Equation 1 suggests that the estimate of an output variable is computed as a combination of all output variables in the database. Their weights depend on the similarity between the input variables p_i of the vector under consideration, and the corresponding input variables p_{ni} pertinent to the sample vectors stored in the database. C_k is a measure of similarity. Consequently, the unknown output variable is determined in such a way that the computed vector composed of the given and estimated data is the most consistent with the sample vectors in the database.

The parameter w is the width of the Gaussian function and is called the smoothness parameter. It determines how fast the influence of data in the sample space decreases with the increasing distance from the point whose co-ordinates are determined by the components (input variables) of the vector under consideration. The larger is the value of w, the more slowly this influence decreases. Large w values exhibit an averaging effect. In principle, a proper value of w should correspond to the typical distance between data points. In this case the CAE method flows a smooth interpolation of the functional relation between the input and the output variables.

In some applications, as it will be shown later, a non-constant value of w flows more reasonable results than a constant value. When using non-constant w values, Equation 1 can still be used, but proper, locally estimated values of w_i should be taken into account. The expression for c_n (see Equation 3) can be rewritten as

$$c_n = \exp\left[-\sum_{i=1}^{L}\frac{\left(p_i - p_{ni}\right)^2}{2w_i^2}\right] \tag{4}$$

in which different values of w_i correspond to different input variables.

It should be stressed that Equations 1 to 3 were derived mathematically[18-20], based on the assumption of a constant uncertainty in the input data. The extension of the applicability of these equations to non-constant w values (Equation 4) is, however, based on physical considerations. Whereas a constant w corresponds to a sphere in an L-dimensional space (L is the number of input variables), a non-constant w value corresponds to a multi-axial ellipsoid in the same space[21-22].

The choice of an appropriate value of w depends not only on the distribution of data, but also on the latter's accuracy, and on the sensitivity of the output variables to change into the input variables. Some engineering judgment, based on know-ledge of the investigated phenomenon, and a trial and error procedure, are needed to determine appropriate value(s) for w.

Training process

The originally proposed procedure[18] that is called CAE in its extended form and is presented here, consists of two parts. The first part corresponds to the so-called self-organisation of the neurons. When using relatively small databases, this part is not needed. The second part represents the mathematical description of different phenomena, using an optimal estimator, as described in previous section. From this point of view training represents a simple presentation of the data to the CAE neural network. In addition, compared to the conventional back-propagation neural networks (BP NN), testing the model is much simpler. Instead of using approximately 70 % of the data for training and the remaining 30 % of the data for testing, a different approach was used. The predicted parameter, i.e. stress of the stress-temperature-strain-strain rate curve, was predicted for each point. In this process the model vector under consideration was temporarily removed from the database. By several trials optimal values of the smoothness parameter were obtained. Recently, tests on phenomenon[28], very different from that presented here, show that such an estimation of the efficiency of the proposed model in general gives more conservative estimates than the conventional approach.

To estimate quantitatively the accuracy of the CAE method for predicting the flow stress curves, the following equation, that enables calculations of the root mean sum of the squared deviations (RMSSD) for each deformation condition, is used:

$$RMSSD = \sqrt{\frac{\sum_{i=1}^{N}\left(\hat{r}_k - r_k\right)}{N}} \tag{5}$$

The prediction is considered good if the RMSSD value is within 5 % of the mean flow stress for that experimental condition[11-12]. The mean flow stress σ_{mfs} is calculated according to

$$\sigma_{mfs} = \frac{1}{\varepsilon}\int \sigma \; d\varepsilon \tag{6}$$

Results for the A2 tool steel show relatively good agreement between the experimental and CAE predicted results (Figures 5). As the relations between the input and the output variables are relatively simple, a constant smoothing parameter can be used (Equation 3). Greater deviations may be observed at smaller strains, where large gradients of the stress curves exist. It should be noted that smaller values of the smoothness parameter w may be used, which will produce better results, but then the interpolation in the strain rate direction will result in a poor overall behaviour of the proposed model. The accuracy attained with the training data ranges from 1.2 % to 6 %, with an average error of 3.6 %. The accuracy of the prediction based on the testing data ranges from 1.4 % to 7.6 %, with an average error of 4.1 %. The errors arising are in general within the required accuracy limits.

The obtained flow stress curves and their CAE predictions with a constant smoothness parameter

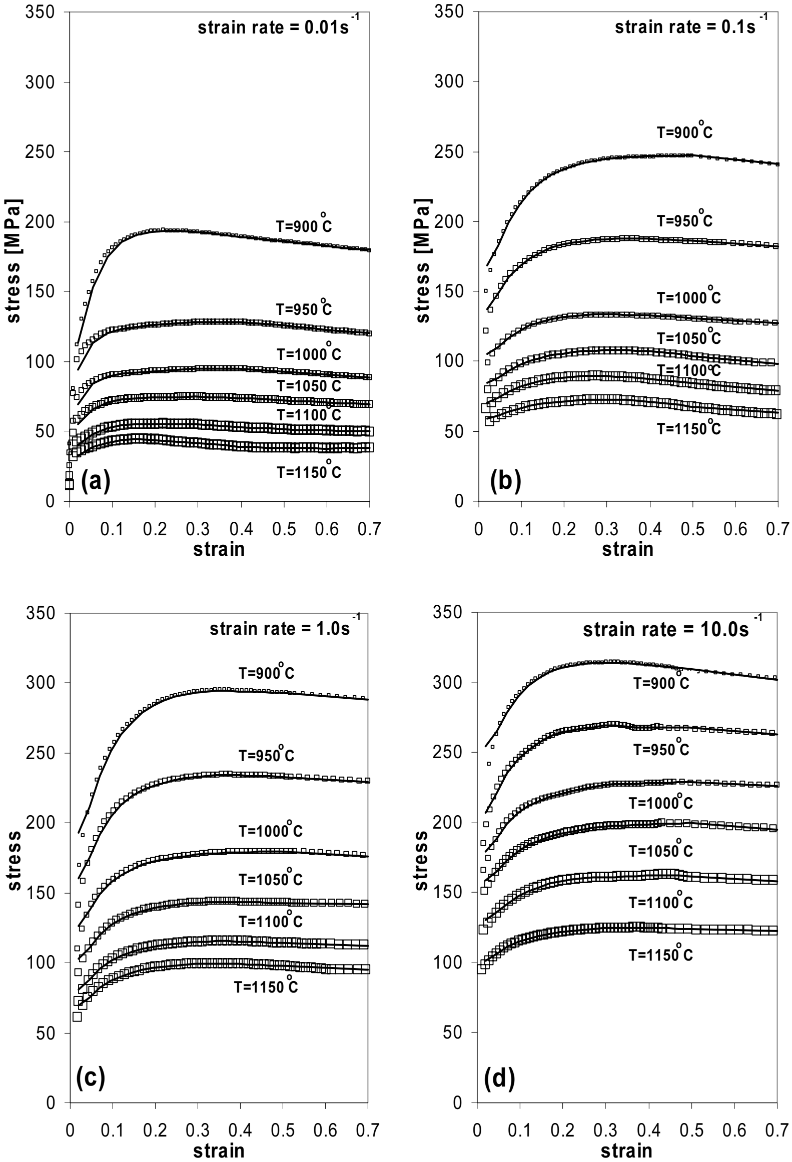

Figure 5. Hot flow stress curves of the AISI A2 tool steel - experimental (□), and the CAE predicted results (–), using a constant smoothing parameter ($w = 0.05$)
Slika 5. Tople krivulje tečenja za orodno jeklo AISI A2 - experimentalne oz. merjene (□) in CAE napovedane vrednosti (–), uporaba konstantnega parametra gladkosti ($w = 0{,}05$)

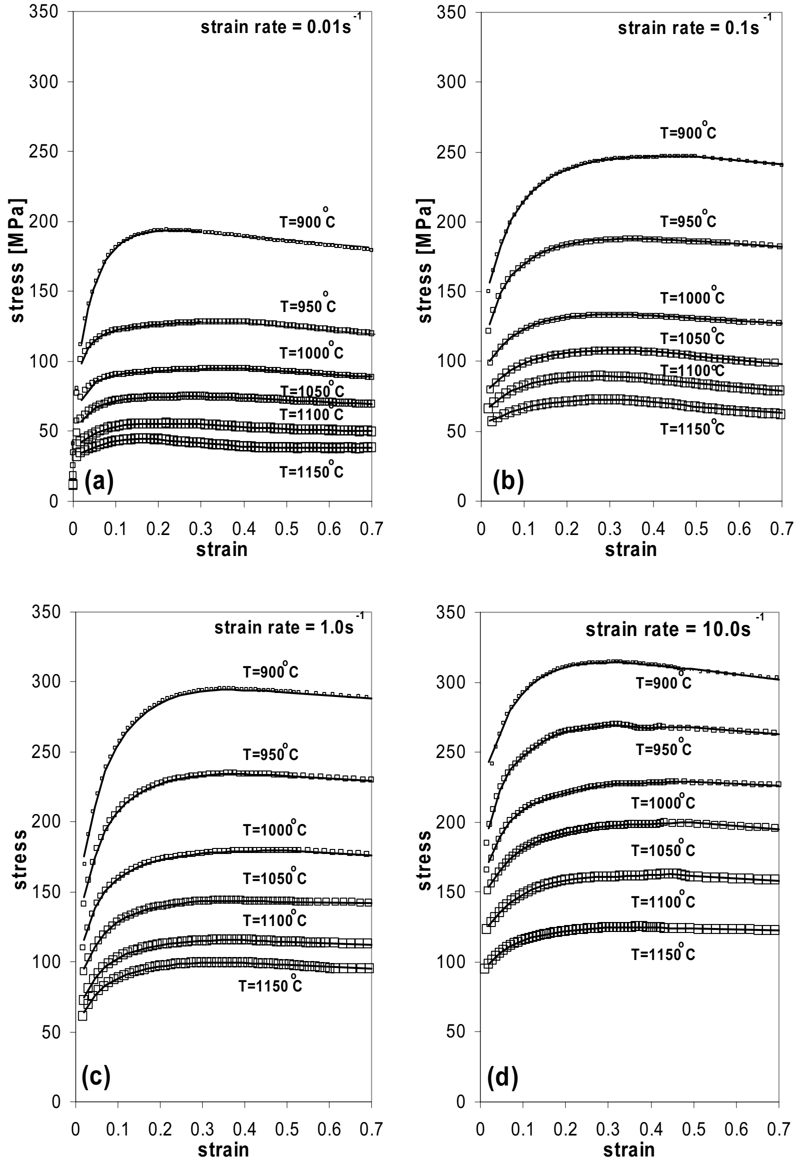

Figure 6. Hot flow stress curves for the AISI A2 tool steel - experimental (□), and the CAE predicted results (–), using a non-constant smoothing parameter ($w_\varepsilon = w_T = 0.03$, $w_{\varepsilon(\varepsilon=0.02)} = 0.01$, $w_{\varepsilon(\varepsilon=0.52)} = 0.03$)

Slika 6. Tople krivulje tečenja za orodno jeklo AISI A2 - experimentalne oz. merjene (□) in CAE napovedane vrednosti (–), uporaba nekonstantnega konstantnega parametra gladkosti ($w_\varepsilon = w_T = 0{,}03$, $w_{\varepsilon(\varepsilon=0{,}02)} = 0{,}01$, $w_{\varepsilon(\varepsilon=0{,}52)} = 0{,}03$)

CAE prediction with a non-constant (elliptical) smoothness parameter

Figures 6 a-d clearly show great improvements in the strain, ranging from 0.02 to 0.1. The results suggest that modelling the flow stress curves may be improved by using a non-constant smoothing parameter (Equation 4). The accuracy achieved with the training data ranges from 0.1 % to 4.3 %, with an average error of around 2.2 %. The accuracy of predictions based on the testing data ranges from 0.2 % to 5.8 %, with an average error of up to 3 %. The errors arising are in general within the required accuracy limit[11-12], and are smaller than that obtained with conventional BP neural networks[3-4].

The ability of CAE NN to interpolate is demonstrated by predicting flow stresses at temperatures and strains over the entire domain in which the model is trained.

Predicting flow stresses for the intermediate input parameters

The real power of the methods for prediction of hot flow stress curves can be clearly recognized from the prediction of the intermediate values of the input parameters. Figure 7a shows the results of the prediction of hot flow stress curves in the direction of the strain rate for $\varepsilon = 0.05$ and $T = 900$ °C. "Experimental" results were calculated from the existing experimental results using linear interpolation (i.e. data points in the neighbourhood of $\varepsilon = 0.05$ for hot flow stress curves at $T = 900$ °C for different strain rates 0.001 s^{-1}, 0.01 s^{-1}, 0.1 s^{-1}, 1 s^{-1} and 10 s^{-1}). Figure 7b shows the results of the prediction of hot flow stress curves in the direction of the strain rate for $\varepsilon = 0.3$ at $T = 925$ °C. Experimental results for temperatures 900 and 950 °C at the strain $\varepsilon = 0.3$ are presented as comparison. CAE prediction seems to be a fair estimate of real hot flow stress curve. Note the semi-logarithmic scale, being logarithmic in the direction of the strain rate.

Figure 7c shows the results of the prediction of hot flow stress curves in the direction of strain for the strain rate 1 s^{-1} and temperature $T = 1025$ °C. Experimental results for temperatures 1050 and 1000 °C at the strain rate 1 s^{-1} are shown as comparison.

Thus this study confirmed the good predictive power of the CAE NN to predict flow stress curves also for intermediate temperatures and strain rates where experimental data existed only for each decade. However, due to the fairly linear relationship between the strain rates and the stresses that might be observed from the "experimental" results, linear rule might be adopted for better agreement. A so called hybrid CAE model for prediction of hot flow stress curves, considering afore mentioned rule, was studied and would be applied in the future.

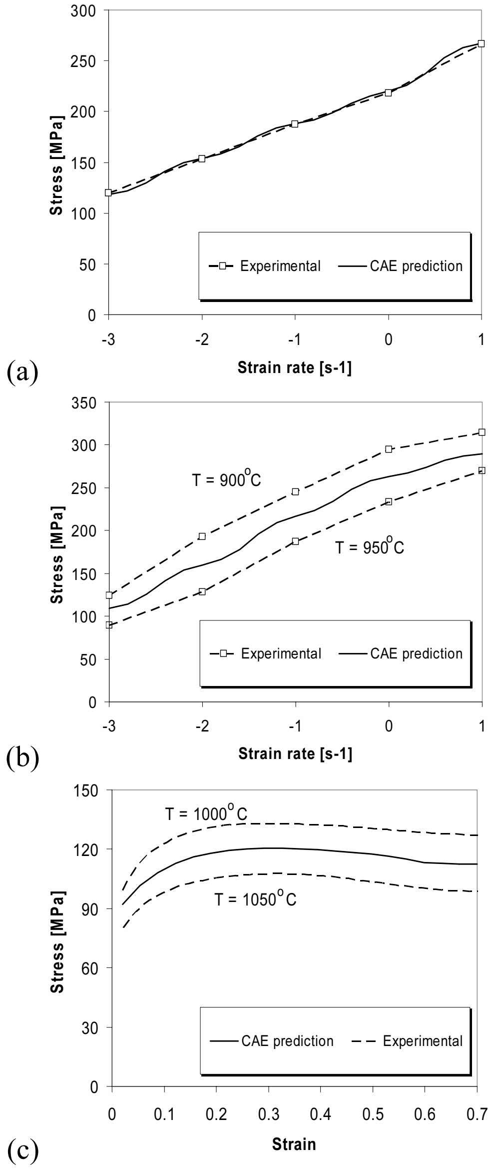

Figure 7. Prediction of hot flow stress curves for material AISI A2 as a function of strain rate for (a) $\varepsilon = 0.05$, $T = 900$ °C, (b) $\varepsilon = 0.3$, $T = 925$ °C and (c) as function of strain for $\varepsilon' = 0.1\ s^{-1}$, $T = 1025$ °C. Non-constant smoothing parameter was used ($w_{\varepsilon'} = 0.1$, $w_T = 0.05$, $w_{\varepsilon(\varepsilon=0.02)} = 0.01$, $w_{\varepsilon(\varepsilon=0.52)} = 0.03$).

Slika 7. Napovedovanje krivulj tečenja za orodni material AISI A2 za (a) $\varepsilon = 0,05$, $T = 900$ °C, (b) $\varepsilon = 0,3$, $T = 925$ °C in (c) kot funkcija deformacije za $\varepsilon' = 0,1\ s^{-1}$, $T = 1025$ °C. Uporabljen je bil nekonstantni parameter gladkosti ($w_{\varepsilon'} = 0,1$, $w_T = 0,05$, $w_{\varepsilon(\varepsilon=0,02)} = 0,01$, $w_{\varepsilon(\varepsilon=0,52)} = 0,03$).

DISCUSSION

Imbert and McQueen[14-15] carried out hot torsion tests on a material of the same grade. These authors obtained somewhat lower values for the flow stress curves. This was expected, since flow stress curves were obtained with torsion tests. The reasons for this discrepancy were firstly a slightly different chemical composition of the tested material, though it was still within permitted limits for the given grade, secondly a different initial microstructure, further, unstable testing conditions, and finally a different heat generation the during deformation of the two types of tests.
The constants were calculated from the maximum flow stresses for different temperatures and strain rates with the hyperbolic sine equation[23-25]

$$Z = \dot{\varepsilon}\exp(Q/RT) = A(\sinh \alpha\sigma)^n \qquad (7)$$

For this purpose, the function χ^2 which determined the difference between measured and calculated values of maximum flow stresses was defined first:

$$\chi^2 = \sum_{i=1}^{N} \frac{(z_i - a_1 x_i - a_2 y_i - a_3)^2}{e_i^2} \qquad (8)$$

where N was the number of measurements, $z_i = \ln(\sinh \alpha\sigma_i)$, $x_i = \ln \dot{\varepsilon}_i$ and $y_i = 10^4 T^{-1}$. Parameter $a_1 = n^{-1}$, $a_2 = 10^{-4} Q n^{-1} R^{-1}$ and $a_3 = n^{-1} \ln A$. When errors were calculated only measurement errors of the parameter z_i, given by $e_i = \alpha\, e_i^{\sigma} \coth \alpha\sigma_i$, where e_i^{σ} were the measurement errors of the flow stresses were taken in account. The details of the minimization procedure of the above expression (8) are given elsewhere[26]. χ^2 had a minimum for Q = 497.5 kJ mol^{-1}, α = 0.0056 MPa^{-1}, n = 6.0 and A = 7.06·10^{19} s^{-1}. The value of the activation energy was higher than that obtained by Imbert and McQueen[14-15]; they obtained the value of 399 kJ mol^{-1} (α = 0.012 MPa^{-1}, n = 3.6). It is also generally known that hot compression tests flow little higher values of activation energies in comparison to the hot torsion tests. Thus, contrary to the claims of some authors[27] that it was not easy to calculate factors α directly from the experimental data, we managed it. For these parameters a comparison between the calculated and the measured relationship between peak stresses and temperatures for five different strain rates is shown in Figure 8a and a comparison between the calculated and the measured peak stresses in Figure 8b. McQueen[13-14] proposed use of an universal value for the coefficient α (α = 0.012 MPa^{-1}) for steels. In our case and for the value of α = 0.012 MPa^{-1} [18-19], it flowed Q = 496 kJ mol^{-1}, n = 4.0, and A = 3.5·10^{15} s^{-1}, but we got worse agreement (χ^2 = 3.5E-001) between the measured and the calculated maximum flow stresses since in our case χ^2 was 1.08E-001.

It is clearly seen From Figure 8a that experimental peak values of flow stress curves at testing temperature 900 °C are higher than the predicted ones. The mean reason is probably precipitation of carbide particles as a very frequent phenomenon in tool steel at temperatures below 1000 ºC[27]. It means that activation energies should be determined for two temperature ranges, i.e. 900 - 1000 ºC and 1000 - 1150 ºC, respectively.

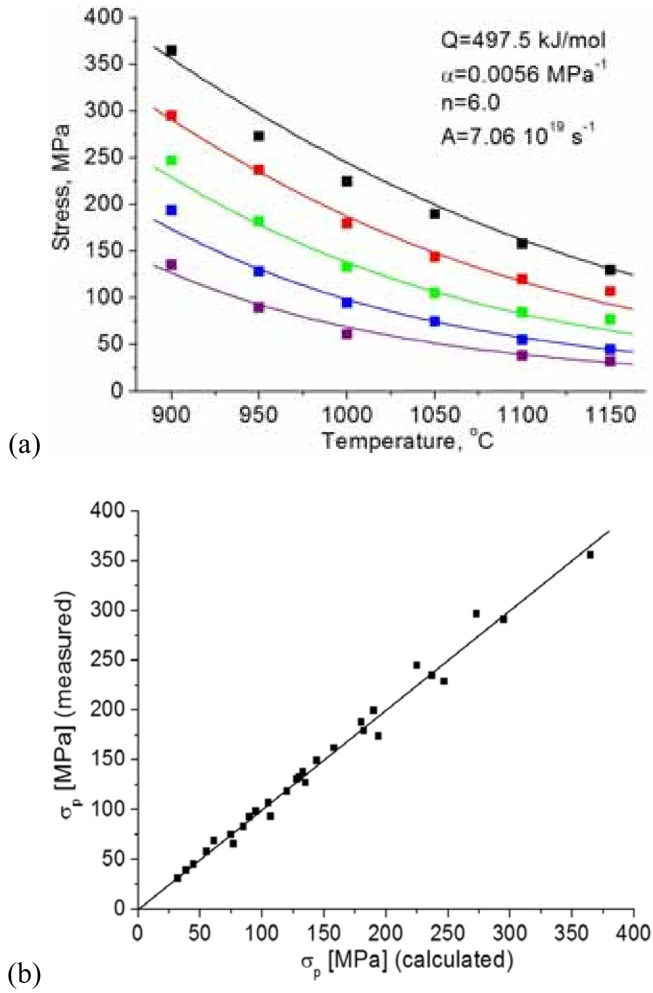

Figure 8. Relationship between peak stresses and temperature of deformation for five different strain rates (from top to bottom: 10 s^{-1}, 1.0 s^{-1}, 10^{-1} s^{-1}, 10^{-2} s^{-1} and 10^{-3} s^{-1}), squares present measured data and full lines the calculated ones (a). Comparison between the measured and the calculated peak stresses (b).

Slika 8. Zveza med maksimumi napetosti in temperaturo deformacije za pet različnih hitrosti deformacije (od spodaj navzgor: 10 s^{-1}, 1,0 s^{-1}, 10^{-1} s^{-1}, 10^{-2} s^{-1} in 10^{-3} s^{-1}), kvadratki predstavljajo merjene vrednosti, polna črta pa izračunane vrednosti (a). Primerjava med merjenimi in izračunanimi maksimumi vrednosti (b).

CONCLUSIONS

For the needs to optimize the hot forming of the AISI A2 tool steel the hot compression tests in the Gleeble 1500D thermo-mechanical simulator were carried out; the test temperatures were in the range (900 - 1150 °C), strain rates (0.001 - 10 s^{-1}) and strains (0 - 0.7). Due to incipient melting, deformations at higher temperatures (1200 °C) should be avoided. This study confirmed the good predictive power of the CAE NN to predict flow stress curves also for the intermediate temperatures and strain rates where experimental data existed only at each decade. Two approaches, namely the method of a constant smoothness parameter and the method of a non-constant smoothness parameter, were examined. The latter gave better results. Hyperbolic sine equation was additionally applied to predict the peak values of flow stresses. Good agreement between the measured and the predicted values was obtained with an exception at the lowest temperature (900 °C, precipitation of carbides). The calculated activation energy (temperature range 900 - 1150 °C) for the AISI A2 was about Q = 497 kJ mol^{-1}. That was a higher value, compared with the values (Q = 399 kJ mol^{-1}, that were obtained with the tangent method based on results of torsion experiments. In cases when precipitation of the carbides at lower temperature range could occur, an activation energy for two temperature ranges should be determined.

POVZETKI

Krivulje tečenja za AISI A2 orodno jeklo

Za potrebe optimiranja tehnologije toplega preoblikovanja, so bili na termomehanskem simulatorju Gleeble 1500D izvedeni stiskalni preizkusi v vročem. Zaradi taljenja evtektičnih karbidov (na višjih temperaturah (cca. 1200 °C)) na kristalnih mejah, preoblikovanje v tem temperaturnem območju zaradi nastanka razpok ni možno. S pomočjo CAE nevronskih mrež so bile zelo uspešno napovedane vrednosti za krivulje tečenja, tako za merjena kot tudi za vmesna (nemerjena) stanja. Dobra prediktivna moč je izkazana tudi za vmesna stanja v polju hitrosti deformacij, saj so tu experimentalni podatki samo na vsako dekado.

Preizkušeni sta bili dve metodi napovedovanja krivulj tečenja z nevronskimi mrežami in sicer motoda s konstantnim ter metoda z nekonstantnim parametrom gladkosti. Slednja daje boljše rezultate. Izračunana je bila tudi aktivacijska energija (Q = 497 kJ mol^{-1}) za celotno temperaturno območje preizkušanja, ki je nekoliko višja kot dobljena iz torzijskih preizkusov (Q = 399 kJ mol^{-1}). Izmerjeni ter izračunani (funkcija sinus hiperbolikus) maksimumi krivulj tečenja se dobro ujemajo na celotnem temperaturnem območju, razen na temperaturi 900 °C. Vzrok za to je verjetno v izločanju sekundarnih karbidov pod temperaturo 1000 °C.

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