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MODELING AND THE RELIABILITY OF CALCULATED FLOW CURVES

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Flow curves are very important input data for numerical modelling of industrial processes and for direct industrial applications. Precise thermal and mechanical testing of low carbon silicon steel showed obvious differences in yield stresses according to permissible oscillations of chemical composition. Since conventional Hajduk, Elfmark and Spittel equations for flow curve calculation are very rigid and cannot describe the local changes of yield stresses caused by phase transformations, a new neural network aproach for modelling the physical phenomena in materials science has been developed. The obtained results showed that neural-network method is a powerful tool, and it can be applied directly in solving problems of materials science (e.g. materials testing support, mathematical simulation of materials forming process).

Key words: *flow curves, neural - network method, low carbon silicon steel*

Modeliranje i pouzdanost izračunatih krivulja tečenja. Krivulje tečenja su vrlo važan ulazni podatak za simuliranje industrijskih procesa s numeričkim metodama i za izravnu upotrebu. Precizno termičko i mehaničko testiranje niskougljičnog silicijskog čelika pokazuje velike razlike naprezanja tečenja između istih čelika s različitim kemijskim sastavom u rangu dozvoljenih tolerancija. Obične jednadžbe za opis krivulja tečenja (Hajduk, Spittel, Elfmark) su ograničene i nemaju mogućnost opisa lokalne promujene naprezanja zbog faznih transformacija. Da bi se rješilo ovaj problem upotrebljena je nova metoda za opis tih procesa - neuronske mreže. Rezultati takve obrade eksperimentalnih podataka pokazuje na veliku sposobnost tih metoda za opis takvih i sličnih procesa u materijalu (potpora testiranju materijala, matematičko simuliranje deformiranja materijala).

Ključne riječi: *krivulja tečenja, metoda neuronskih mreža, nisko ugljični silicijski čelik*

INTRODUCTION

A reliable treatment of natural phenomena is based on measurements and the description, based on relations between the observed results. From the theoretical point of view, the relations are the most appropriately specified in terms of abstract mathematical models representing mathematical laws [1]. But from the practical point of view, simulated analogue models, based on electronic devices are sometimes more convenient. The aim of this paper is thus to introduce a generalized interpretation of description of phenomena which can be realised by a (personal) computer.

It should be noted that in the process of modelling phenomena we want to describe complex reality on the one side with simple, usually very simplified, abstract mathematical models on the other side (Figure 1.) [2], where:

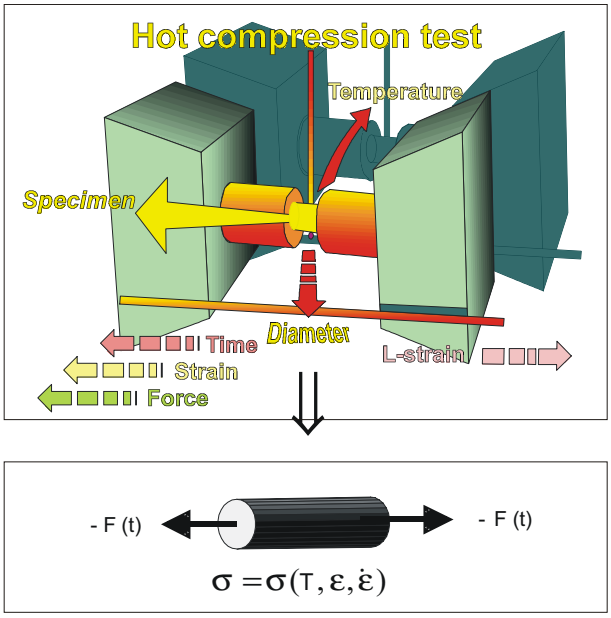

Figure 1. **Descripton of reality with an abstract mathematical model**
Slika 1. **Opis realnog stanja sa sažetkom matematičkog modela**

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$F(t)$ - time function of compression force, σ - stress in material, ε - strain, $\dot{\varepsilon}$ - strain rate.

Mathematical description of different phenomena in materials science is naturally very complex. Various materials and mechanical quantities are functions of different parameters (temperature, strain, strain rate, microstructure), and the relations between them are usually highly nonlinear. Therefore, the aim of this paper is to present a new approach, called a neural - network system, in different applications, known also as CAE (Conditional Average Estimator). The intention of the authors is to show that the method is simple for use, computationally effective and very successful in describing the phenomena compared to the conventional approximation techniques.

EXPERIMENTAL

Laboratory measurements included standard hot tensile and compression tests on the Gleeble 1500 physical simulator. Specimens have been made of four different melts of low carbon silicon steel. For hot compression tests, standard Rastegaev cylindrical specimens with dimensions $2r = 10$ mm, $h = 12.5$ mm (12 mm bulk with 2 x 0.25 mm furrow for lubrication, graphite) were used, while the preliminary high temperature dilatation tests have been done using standard cylindrical tensile specimens.

The main chemical composition of specimen is presented in Table 1..

Table 1. **The chemical composition of four different melts of low carbon silicom steel**
Tablica 1. **Kemijski sastav četiriju različitih talina nisko ugljičnih silicijskih čelika**

	% C	% Si	% Mn	% Cr	%Al
EV15-78	0.012	1.38	0.21	0.17	0.224
EV15-74	0.015	1.64	0.18	0.16	0.393
EV15-84	0.013	1.32	0.28	0.45	0.186
EV15-82	0.015	1.38	0.26	0.15	0.238

The influence of chemical composition on the temperature of $\alpha \rightarrow \gamma$ phase transformation is presented in Table 2..

Table 2. **Critical temperatures, which indicate the beginning and the ending of phase transformation for four different melts of low carbon silicom steel**
Tablica 2. **Kritična temperatura početka i kraja fazne transformacije četiriju različitih talina nisko ugljičnog silicijskog čelika**

	T_{start} [°C]	T_{end} [°C]	ΔT [°C]
EV15-78	975	875	100
EV15-74	915	785	130
EV15-84	879	822	57
EV15-82	903	827	76

The program of hot compression tests is shown in Table 3..

Table 3. **Testing parameters of hot compression tests**
Tablica 3. **Parametri testiranja toplog tlačnog pokusa**

Strain	strain rate [s^{-1}]	temperature [°C]
0-0.6	0.1, 1, 5, 10	1200
0-0.6	0.1, 1, 5, 10	1100
0-0.6	0.1, 1, 5, 10	1000
0-0.6	0.1, 1, 5, 10	950
0-0.6	0.1, 1, 5, 10	900
0-0.6	0.1, 1, 5, 10	850
0-0.6	0.1, 1, 5, 10	800
0-0.6	0.1, 1, 5, 10	750
0-0.6	0.1, 1, 5, 10	700

Thermal and mechanical tests have been fully computer controlled. During each test, the following actual values have been measured: specimen diameter, specimen length, piston stroke, force, and specimen temperature. Simultaneously true stresses, true strains and strain rates have been calculated. In order to reduce the thermal gradient along the specimen, a new isothermal tool set has been used. Acceleration and retardation effects at high piston rates (strain rates of 10 s^{-1}) have been considered in the evaluations of measured data. Typical true stress - true strain curves obtained with hot compression tests are shown in Figure 2..

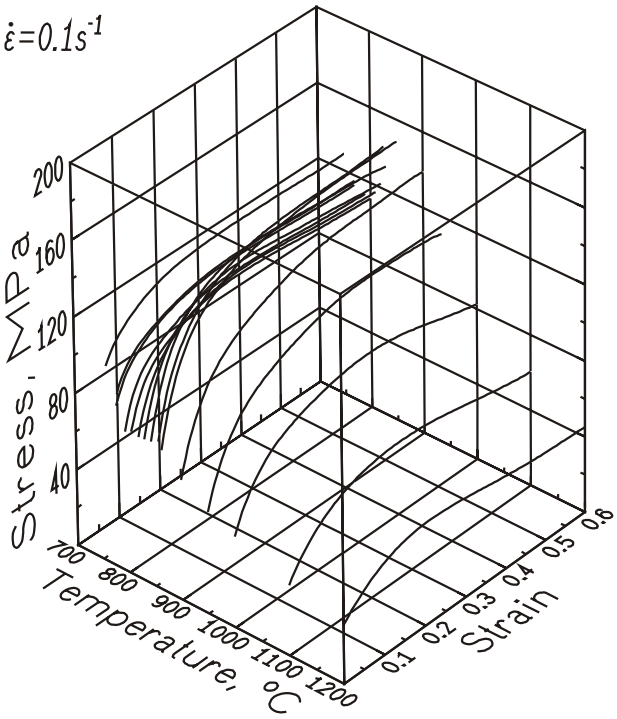

Figure 2. **Typical true stress - true strain curves for low carbon silicon steel for strain rate of 0.1 s^{-1}**
Slika 2. **Tipična krivulja naprezanje - deformacija za nisko ugljični silicijski čelik za brzinu deformacije 0.1 s^{-1}**

Next to the deformation temperature, yield stress depends also on strain rate.

Temperature, strain, and strain rate are standard parameters, which should be considered in any calculation

or approximation of flow curves. More complex influenced parameter represent chemical composition which cannot be controlled, and varied random by from a melt to melt.

Chemical composition has high influence on the yield stress at different strains. Even at very low strains, the variations are obvious, as shown in Figure 4..

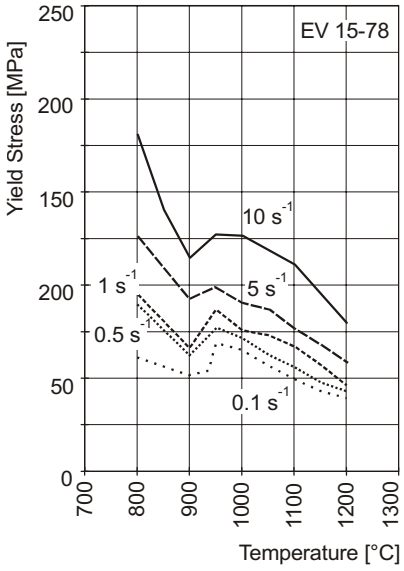

Figure 3. **Yield stress versus temperature for low carbon silicon steel**

Slika 3. **Naprezanje tečenja u ovisnosti o temperaturi za nisko ugljični silicijski čelik**

Conventional equations for calculation of flow curves are rigid and cannot describe the changes of yield stresses caused by phase transformations. Figure 5. shows measured yield stresses, and yield stresses calculated with Hajduk-Elfmark equation [3]:

$$k_f = k_f(T, \acute{I}, \acute{f}) = \\ = k_{f0} A_1 e^{-m_1 \cdot T} A_2 \varepsilon^{m_2} e^{-m_3 \cdot \varepsilon} A_3 \dot{\varepsilon}^{m_4} A_4 (1+\varepsilon)^{m_5 \cdot T} A_5 \dot{\varepsilon}^{m_8 \cdot T} \quad (1)$$

with: k_f - yield stress,
k_{f0} - yield stress for standard conditions,
T - temperature,
ε - strain,
$\dot{\varepsilon}$ - strain rate,
A_1, A_2, A_3, A_4, A_5 - coefficients of equation,
$m_1, m_2, m_3, m_4, m_5, m_8$ - coefficients of equation.

Equations based on the Hajduk's model could not describe the changes of yield stress in the temperature range of phase transformation [4].

We have tested several equations based on the Hajduk's model, but because of the exponent nature, these equations have very similar behaviour. There were found differences in the 2D area, e. g. when describing the measured true stress/true strain curves, obtained at a constant strain rate. When these equations were applied for the 3D space local changes of yield stress, caused with dynamic recovery, dynamic recrystallization, and phase transformations could not be described. The adaptiliby of the following equations was compared:

a) Hajduk:

$$k_f = k_{f0} A_1 e^{-m_1 \cdot T} A_2 \varepsilon^{m_2} A_3 \dot{\varepsilon}^{m_3} \quad (2a)$$

b) Hajduk-Spittel:

$$k_f = k_{f0} A_1 e^{-m_1 \cdot T} A_2 \varepsilon^{m_2} e^{-m_3 \cdot \varepsilon} A_3 \dot{\varepsilon}^{m_4} \quad (2b)$$

c) Hajduk-Elfmark:

$$k_f = k_f(T, \acute{I}, \acute{f}) = \\ = k_{f0} A_1 e^{-m_1 \cdot T} A_2 \varepsilon^{m_2} e^{-m_3 \cdot \varepsilon} A_3 \dot{\varepsilon}^{m_4} A_4 (1+\varepsilon)^{m_5 \cdot T} A_5 \dot{\varepsilon}^{m_8 \cdot T} \quad (2c)$$

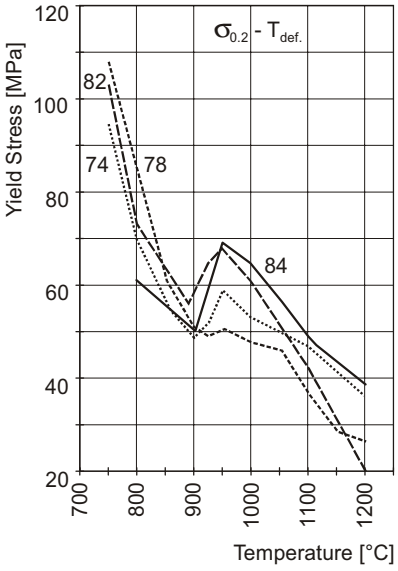

Figure 4. **The variation of yield stress with four different chemical composition of low carbon silicon steel (Table 1.) for the strain rate of 0.1 s^{-1}, and strain of 0.002**

Slika 4. **Promjena krivulja napona tečenja za četri razna kemijska sastava nisko ugljičnog silicijskog čelika za brzinu deformiranja od 0.1 s^{-1} i deformaciju 0.002**

It was possible to use upper equations when the critical temperatures were determined and the whole thermo-mechanical space was divided into characteristic regions. For each region, their own flow curves were calculated. On the other hand this problem has been solved using a new intelligent neural-network method for flow curves calculation. Upper figure shows that there exists adaptability to almost any changes of yield stress. Of course, also this calculation was based on laboratory measurements. Let us introduce some theoretical backgrounds.

ON THE MODELLING OF PHENOMENA

A two-dimensional problem, as shown in Figure 6a is assumed. The phenomenon, which may be interpreted as behaviour of low carbon silicon steel at different strains, strain rates, and temperatures, is partly described (at constant strain and strain rates) by five measured points in the X-Y plane. It is clear that an infinite number of dif-

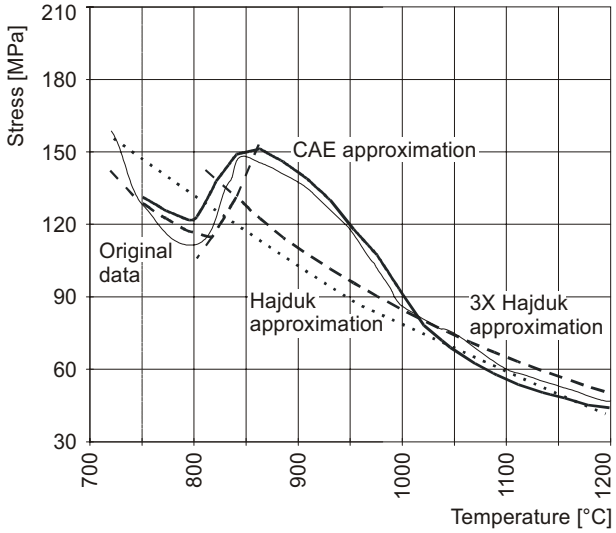

Figure 5. **Three different calculation of yield stresses for the strain rate of 0.1 s^{-1}, and the strain of 0.6 (low carbon silicon steel)**

Slika 5. **Tri različita matematička opisa naprezanja tečenja za brzinu deformiranja 0.1 s^{-1}, pri deformaciji 0.6 (nisko ugljični silicijski čelik)**

ferent mathematical curves can pass through these five points. Therefore, the main question here is what is the mathematical rule, which optimally describes the phenomenon.

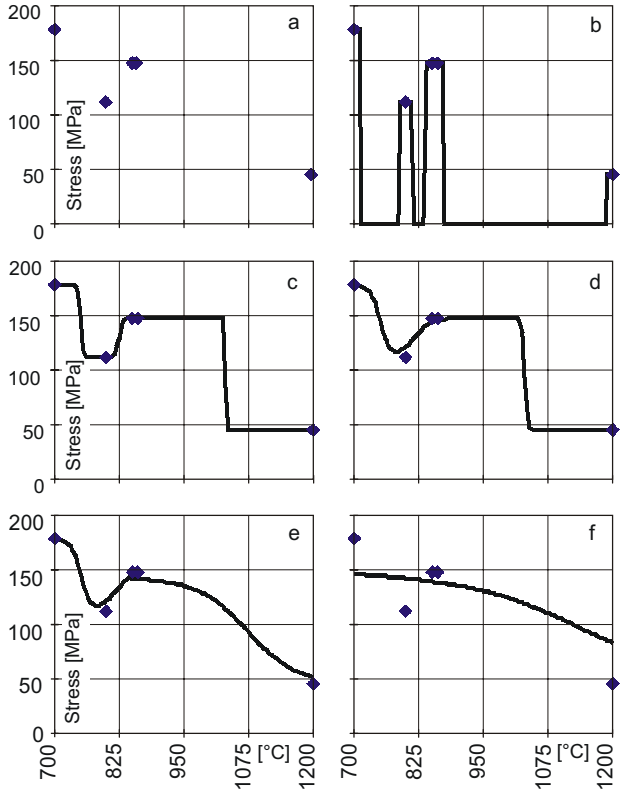

Figure 6. **Graphic presentation of the description of phenomenon at different desired precision**

Slika 6. **Grafički prikaz opisa utjecaja različitih preciznosti opisa nekog fenomena**

At first, it was assumed that a high degree of precision was wanted. The mathematical description (in form Y = Y(X)) of the phenomenon in this case is shown in Figure 6b. With exception of five fixed points we do not know anything about the phenomenon, therefore the Y values left and right of fixed points are set to zero. Such a model can not satisfactorily describe the entire phenomenon. Thus, we were proceeding with an assumption of a lower degree of precision. The result is shown in Figure 6c. It is supposed that natural phenomena are usually continuous; the presentation in Figure 6c seems not to be a very good one, still less the optimal description of the phenomenon. Figure 6d shows the result at even lower degree of precision. It can be seen that curve becomes continuous, smoother, and optically more acceptable. Degree of precision based on an engineering judgement, represented by the curve in Figure 6e seems to be the best representation of natural phenomenon, described by discrete points. Further decreasing of the degree of precision leads to smoothing of the curve (Figure 6f), which in final stage becomes a horizontal line. It should be noted that no known informations about the phenomenon are taking into account (except that

Table 4. **Comparison between CAE and back propagation neuronal networks**

Tablica 4. **Usporedba između CAE i povratnog prodiranja neuronskih mreža**

CAE NN	BP NN
Learning is very simple it corresponds to the presentation of model vectors to the CAE NN.	Learning is pretentious and corresponds to the cyclic presentation of model vectors to BP NN and adaptation of network in each cycle.
Learning process is very short; ordinary PCs can be used for very complex problems.	Learning process is time consuming; very complex problems demands special hardware and parallel computing.
Description of the phenomena problem solution depends on the smoothing parameter only!	Description of the phenomena problem solution depends on many variables number of hidden layers, number of neurons in each layer, learning coefficients, …
Number of hidden layers is fixed (2), and CAE is still able to correctly describe the highly non-linear problems.	Number of hidden layers depends on the complexity of the problem in general, more complex problem, more hidden layers and neurons in those layers are needed.
Number of neurons depends on the number of model vectors and number of variables, that describe the phenomenon (this can be very high).	Number of neurons is indepenndt on the number of model vectors and number of variables, that describe the phenomenon.
Improvement of the model is very simple and instantaneous, when the data base is improved.	Improvement of the model demands re-learning, with (probable) modification of network learning parameters.
Complex real-time applications with greater number of variables are possible only after applying self-organisation process.	Complex real-time applications with greater number of variables are dirrectly applicable.

the phenomenon is "properly smooth"), and that the modelling is entirely based on the measured data. The above example [2] has been shown for illustration purpose only.

Modelling (description) of the phenomenon, presented in Figure 6. can be simply simulated by CAE. Precision is directly correlated to the so-called smoothing parameter *w*, and to the learning error in the classical back - propagation neural networks, which is usually defined as an average error. The curve in the case of two-dimensional problems, or hyper-surface in the case of multi - dimensional problems, which graphically represent the mathematical description of the phenomenon, can be calculated in discrete points by simple expression as a function of the smoothing parameter *w* [5-8].

In Table 4. the differences between CAE and classical back-propagation neural networks are shown.

MODDELING OF HOT YIELD STRESS CURVES FOR LOW CARBON SILICON STEEL

Mathematical description of hot yield stress curves is a function of different parameters as temperature, strain and strain rate, microstructure etc. Shape of hot yield stress curves (surfaces) is complicated due to the microstructural changes, which occur during the hot working process. Also, phase transformations influence yield stress. Because of thermal gradient, barrelling or necking, and friction, which influence the disparities in temperature, strain, and strain rates in the specimen volume, different evaluations of experimental data are needed. The most popular model for yield stress curves is based on multiplying the input specific coefficient with the specific coefficients for temperature, strain, and strain rates [3]. In this section, CAE will be applied to the same problem.

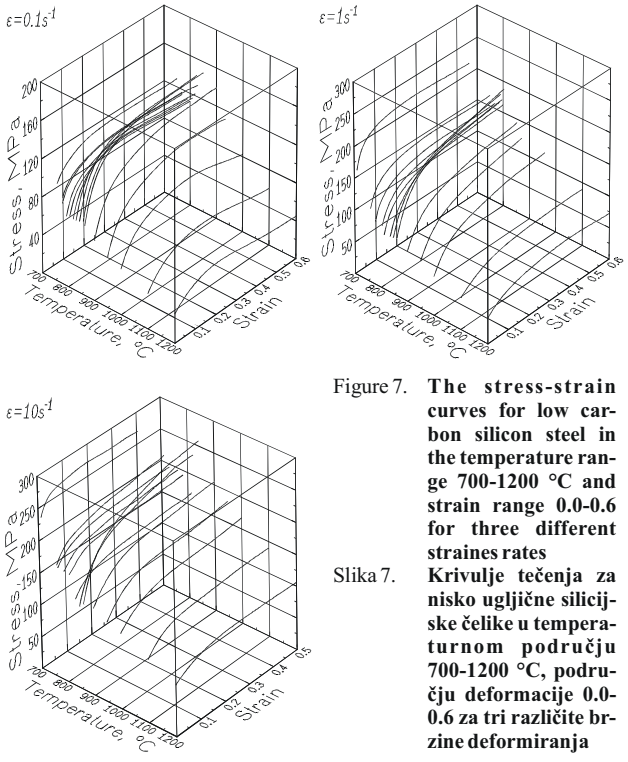

Figure 7. **The stress-strain curves for low carbon silicon steel in the temperature range 700-1200 °C and strain range 0.0-0.6 for three different straines rates**

Slika 7. **Krivulje tečenja za nisko ugljične silicijske čelike u temperaturnom području 700-1200 °C, području deformacije 0.0-0.6 za tri različite brzine deformiranja**

The data base consists of measured data at discrete strain and temperature points for three different values of strain rates. Experimental data are graphically presented in Figure 7.. For the modelling, smoothing parameters w_i, linearly dependent on temperature and strain, were used [9-10].

Absolute values of function gradients very approximately corresponded to the linearity rule. As parametric studies show, CAE is not sensitive on the use of approximate value for w_i different from linear. However, a relatively simple assumption (selection of smoothing parameter) gives good results. Figure 8. shows measured stress-strain curves and two results of two different modelling techniques. Figure 8b shows the results of three independent calculations by Hajduk [3], related to three specific regions (700 °C - 800 °C, 800 °C - 850 °C, 850 °C - 1200 °C), and defined by characteristic behaviour of yield stress. Figure 8c shows the result of CAE which closely follows the original data. The solution is better and more smooth than in the case of Hajduk's model. Calculation of yield stress curves by CAE has not been optimised yet. Despite this, it gives good results, and compared to Hajduk's calculation, they are even better. By optimising the calculation and by acquiring the necessary characteristic experimental data, CAE will be used for reducing the number of mechanical tests.

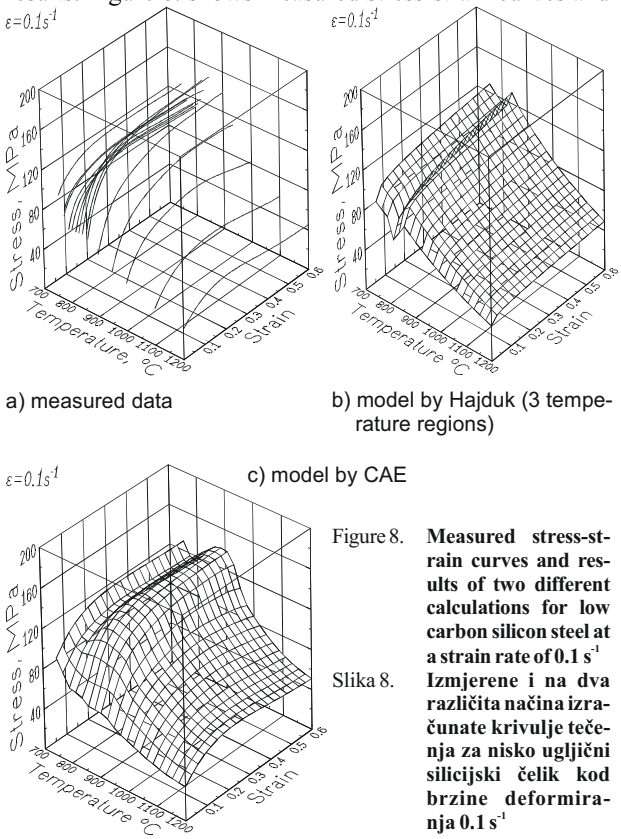

Figure 8. **Measured stress-strain curves and results of two different calculations for low carbon silicon steel at a strain rate of 0.1 s^{-1}**

Slika 8. **Izmjerene i na dva različita načina izračunate krivulje tečenja za nisko ugljični silicijski čelik kod brzine deformiranja 0.1 s^{-1}**

CONCLUSIONS

Flow curves indicate different changes in metals which occur during hot deformation. Conventional equations for calculation of flow curves are convenient because they can be used in any mathematical operation. The main disadvantage of equations based on the Hajduk model is that they cannot describe local changes caused by dynamic softening processes and phase transformations. On the other hand allowed variations of chemical composition can increase or decrease the yield stress for more than 20 %.

Therefore an intelligent, neural network-like system, known as CAE, has been proposed for modelling of different phenomena in materials science [9]. The results shown in the paper demonstrate that such empirical description is a very powerful tool. Because the principle of minimising the statistical error has been incorporated, CAE is rather robust and insensitive to small disturbances in the measured data. In general, no *a priori* informations about the phenomenon are included in the modelling. In some cases, by taking into account *a priori* information, CAE can eventually better fit particular phenomenon. This can be done in few ways, either by prescribing the dependence of smoothing parameter w_i or by artificial generation of additional data (using different physical assumptions). CAE has several advantages compared to the so far used expressions:

- the relations between input and output variables (parameters) are not needed to be *a priori* selected by a predictive rule. This is very important in the case when we do not know much about the phenomenon;
- it takes into account the currently available data base which can be continually supplemented by new test results, and adjusted according to the needs of the user;
- an arbitrary number of input variables (parameters) can be taken into account. The result of decreased number of input variables is an averaging effect;
- the same method can be directly, with some minor changes and improvements in order to better fit into particular phenomenon, applied to similar problems in materials science.

Future work will be focused on further developing and optimising CAE for particular phenomena. By acquiring the necessary characteristic experimental data, CAE, simultaneously with use of expert system [11], will be used for reducing the number of mechanical tests in describing hot yield stress curves. Additional input parameters (ratios of important chemical elements, contained in steel) will be taken into account.

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