A HOT FLOW CURVE APPROXIMATION VIA BIOLOGY-INSPIRED ALGORITHMS

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Abstract

Biology-inspired algorithms represent a set of various techniques which can be used e.g. in the case of high-nonlinear approximation tasks. In the presented research, this kind of algorithms was utilized to approximate the experimental flow curve dataset of the micro-alloyed manganese-vanadium steel. Two methodically different representatives, namely a genetic algorithm optimization and an artificial neural network approach, were applied for this purpose. In the first case, a genetic-algorithm-optimization technique was used to calculate the material constants of two flow stress models. These models were then applied to describe the flow curves of the examined steel. In the second case, an artificial neural network was assembled, adapted and used to deal with the flow curve approximation issue. Graphical results have showed a high accuracy with respect to both approximation methods. Nevertheless, the following statistical evaluation has revealed a much higher fit in the case of the proposed neural network approach.

Keywords: Hot flow curve approximation, genetic algorithm, artificial neural network

1. INTRODUCTION

Since the end of the last century, biology-inspired algorithms have been being extensively used to enhance the solution of complex scientific and engineering issues, for instance highly nonlinear approximation tasks [1]. In the field of material forming, so-called hot flow curves are a typical representative of this kind of approximation problem. In the case of formed (e.g. rolled or forged) material, these curves illustrate a flow stress development under different thermomechanical circumstances (such as strain, strain rate and deformation temperature) - see **Figure 1** for illustration [2]. These dependencies are compiled on the basis of experimentally acquired datasets (typically originating from torsion or uniaxial compression tests), and an approximation process then allows the flow stress prediction under non-experimental conditions.

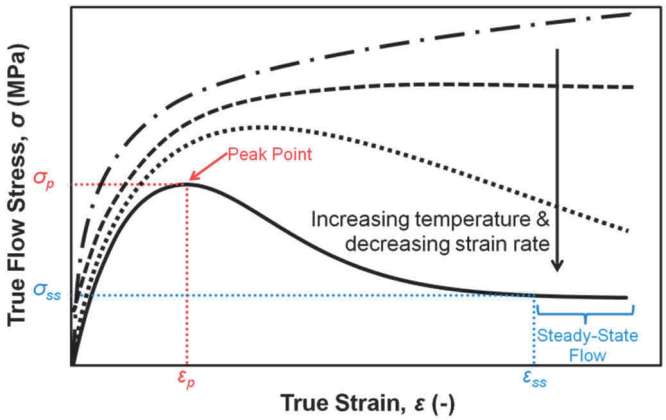

Figure 1 Schematic illustration of hot flow curve types

This approximation is usually performed by means of previously derived flow stress models [2, 3]. However, an accuracy of these models is highly dependent on the calculation of material constants. Of course, these constants are often calculated through the numerical techniques (such as gradient algorithms [4]) because of the nonlinearity of the flow stress models. Moreover, searching for optimal values of material constants can be also alternatively realized by means of so-called genetic-algorithm (GA) optimization [5, 6]. This heuristic evolutionary algorithm is inspired by the genetic principles and natural selection theory which were formulated by Ch. Darwin (1859) [7]. Nevertheless, there is also a biology-inspired approach which allows exclusion of the flow stress models from the approximation procedure, so they do not have to be used at all. So-called artificial neural network (ANN) approach [8, 9] can be used to deal with theoretically every approximation issue.

It is inspired by the Spencer's description of information processing in the brain neural network (1872) [10]. In the submitted manuscript, the Cingara & McQueen's flow stress model and its modification are used to approximate an experimental hot flow curve dataset of the manganese-vanadium steel. The GA optimization is utilized to find proper material constants. In addition, the examined dataset was also approximated via the ANN approach. The experimental conditions were as follows: deformation temperatures (1123 K, 1273 K, 1373 K, 1473 K and 1553 K), strain rates (0.1 s^{-1}, 1 s^{-1}, 10 s^{-1} and 100 s^{-1}) and the true strain up to 1.0. The whole experimental procedure was described previously in [11]. The aim of this research is to compare the accuracy of both proposed methods and their prediction capability beyond the experimental conditions.

2. FLOW CURVE APPROXIMATION VIA FLOW STRESS MODELS WITH GA OPTIMIZATION

The well-known Cingara and McQueen's model [12] is designed to approximate the flow curves in the strain range of $0 \leq \varepsilon \leq \varepsilon_p$, i.e. up to the peak point (**Figure 1**) - see equation (1). The modification of this model [11] is then intended to cover the strain range of $\varepsilon_p \leq \varepsilon$, i.e. beyond the peak point - see equation (2):

$$\sigma = \sigma_p \cdot \left[\frac{\varepsilon}{\varepsilon_p} \cdot \exp\left(1 - \frac{\varepsilon}{\varepsilon_p}\right)\right]^c \tag{1}$$

$$\sigma = \sigma_{ss} + \left(\sigma_p - \sigma_{ss}\right) \cdot \left[\frac{\varepsilon}{\varepsilon_p} \cdot \exp\left(1 - \frac{\varepsilon}{\varepsilon_p}\right)\right]^s \tag{2}$$

In equations (1) and (2), σ (MPa) is the flow stress level (dependent variable) and ε (-) is the true strain (independent variable). The presented models contain auxiliary variables (parameters), namely the peak strain, ε_p (-), peak stress, σ_p (MPa), steady-state stress, σ_{ss} (MPa), hardening exponent, c (-), and softening exponent, s (-). These parameters are dependent upon strain rate and deformation temperature. The experimental values of ε_p, σ_p and σ_{ss} are deducted from the experimental σ - ε curves (clearly marked in **Figure 1**). The experimental values of c and s are then achieved by means of regression analysis of the logarithmic expressions of equations (1) and (2) [11,12]. It is quite obvious that an accurate approximation of these parameters plays a key role in the case of performance of models (1) and (2). Different equations have been proposed to individually approximate each mentioned parameter. Nevertheless, the following equation (3) represents the relationship which has a capability to universally describe each above mentioned parameter [11]:

$$y_i(\dot{\varepsilon}, T, p) = p_1 \cdot \dot{\varepsilon}_i^{\,p_2 - p_3 \cdot \frac{1}{T_i}} \cdot \exp(-p_4 \cdot T_i) \tag{3}$$

The dependent variable $y_i(\dot{\varepsilon}, T, p)$ is always one of the described parameters. The independent variables $\dot{\varepsilon}_i$ (s^{-1}) and T_i (K) represent the strain rate and deformation temperature, respectively. Note, the $i = [1, n] \subset \mathbb{N}$ is the i-th $\dot{\varepsilon}$-T combination (n = 20). Equation (3) also contains four material constants - p_1 (various), p_2 (-), p_3 (K) and p_4 (K^{-1}) - which have to be calculated [11]. In this research, optimal values of these constants were found on the basis of minimization of MSE (Mean Squared Error [13]) performance function:

$$\min_p \mathrm{MSE} = \frac{1}{n} \cdot \sum_{i=1}^{n} \left[p_1 \cdot \dot{\varepsilon}_i^{\,p_2 - p_3 \cdot \frac{1}{T_i}} \cdot \exp(-p_4 \cdot T_i) - y_i\right]^2 \tag{4}$$

In equation (4), y_i represents i-th experimental value of given parameter. The minimization process was performed via GA optimization as is illustrated in **Figure 2**. The genes represent the values of the material constants, i.e. p_1, p_2, p_3 and p_4. A specific set of these constants (genes) is labeled as an individual. The population is then the set of various individuals. It is clear, each individual in the population represent a possible solution of the minimization issue. The genetic algorithm is an iterative heuristic process which is based on the generation of high amount of different individuals. Each iteration step creates a new population, and each individual of the newly created population is evaluated with respect to equation (4). The algorithm runs ad infinitum until the predefined termination settings are reached - e.g. the value of MSE is smaller or equal to

that required, or a maximum of iterations was achieved. New populations are created on the basis of three operators (selection, crossover and mutation) - in detail described in [6]. Resulting values of examined material constants are listed in **Table 1**.

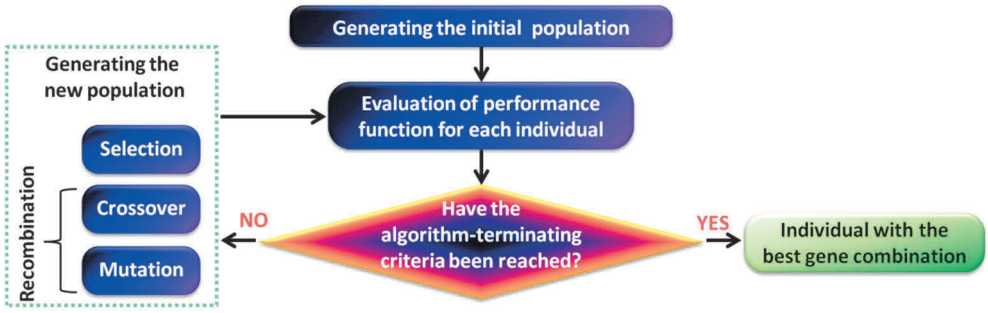

Figure 2 Schematic illustration of the genetic algorithm optimization

Table 1 The values of the material constants of equation (3) after the genetic algorithm optimization

Constant / Parameter	ε_p	σ_p	σ_{ss}	c	s
p_1 (various)	$2.73 \cdot 10^{+1}$	$1.22 \cdot 10^{+4}$	$1.92 \cdot 10^{+4}$	$3.25 \cdot 10^{-2}$	$2.03 \cdot 10^{+1}$
p_2 (-)	$4.36 \cdot 10^{-1}$	$4.74 \cdot 10^{-1}$	$5.66 \cdot 10^{-1}$	$1.01 \cdot 10^{-1}$	$3.51 \cdot 10^{-1}$
p_3 (K)	$3.50 \cdot 10^{+2}$	$4.22 \cdot 10^{+2}$	$5.17 \cdot 10^{+2}$	$3.06 \cdot 10^{+2}$	$2.55 \cdot 10^{+2}$
p_4 (K^{-1})	$3.33 \cdot 10^{-3}$	$3.64 \cdot 10^{-3}$	$4.06 \cdot 10^{-3}$	$-1.78 \cdot 10^{-3}$	$1.11 \cdot 10^{-3}$

3. FLOW CURVE APPROXIMATION VIA ANN APPROACH

In comparison to the above introduced flow stress models, an artificial neural network approach offers a universal approximation solution. The flow stress models are limited by their fixed mathematical structure, while an ANN architecture is built as a network of variable number of neurons (computational units) [14]. The experimental hot flow curve dataset of the investigated steel has been approximated via Multi-Layer Feed-Forward Artificial Neural Network with the Back-Propagation (BP) learning algorithm (**Figure 3**).

The proposed network connects the independent variables (i.e. strain, strain rate and deformation temperature) with the dependent variable (i.e. flow stress) via four-layer network of artificial neurons. The neurons of each layer are connected with the neurons of the neighboring layers by the synaptic weights, *w* (-). In addition, the neurons of the hidden and output layers are associated with the so-called bias value, *b* (-). The input layer is intended only for implementation of independent variables into the network - no calculations run inside the input neurons. In the contrary, neurons of the hidden and output layers represent the main computational units [9].

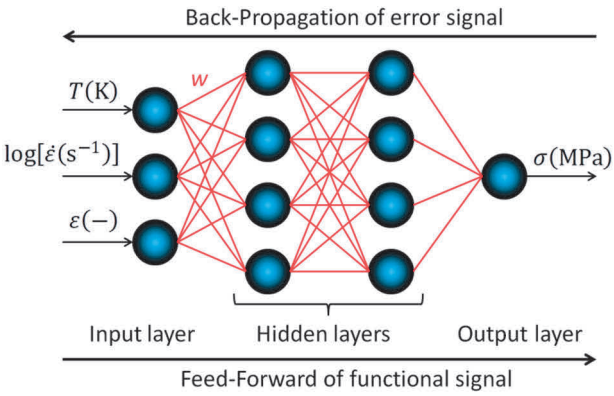

Figure 3 Architecture of the proposed neural network

The process of the calculation of the output variable (i.e. flow stress) via the proposed type of the neural network is called as the feed-forward of functional signal - described in [14]. Nevertheless, the proposed network has to be adapted before its practical use. This process ensures the correct response of the network (close as possible to the target values). A key role of the adaptation process is represented by a training

procedure. The aim of the network training is to find a proper set of *w*-values and *b*-values in order to minimize the performance function - mean squared error (MSE [13]) in the case of this research. It is highly important, the trained network has to allow the prediction beyond the experimental conditions, i.e. the network must not be overtrained. The back-propagation of error signal [15] and the Levenberg-Marquardt optimization algorithm [16,17] in combination with the Bayesian regularization [18,19] were employed to deal with this issue. The training process should be applied at different network architectures, i.e. under various numbers of hidden layers and neurons inside them. The proper architecture is, of course, selected on the basis of the smallest returned MSE-value [20]. In the case of this research, two hidden layers with four neurons in each layer were found to be appropriate - see **Figure 3** for illustration.

4. RESULTS AND DISCUSSION

The color curves in **Figure 4** represent the graphical comparison among the experimental (boxes) and two calculated (lines) datasets. The dashed lines embody the curves which have been calculated on the basis of above introduced flow stress models with GA optimization, while the full lines symbolize the proposed ANN approach. In addition, there is another flow curve dataset (gray dashed and full lines) which represent the prediction beyond the experimental conditions (specifically at the temperature levels of 1173 K, 1223 K, 1323 K and 1423 K). The aim of this additional dataset is to verify the prediction capability of utilized approximation methods. The charts in **Figure 4** clearly show that the both approaches have a high ability to describe the experimental data. The ANN description, however, seems to be slightly better (see e.g. 1273 K and 0.1 s^{-1}. The predicted curves (gray lines) also exhibit a high appropriateness in the case of both methods - each predicted curve seems to be in the presumed temperature level.

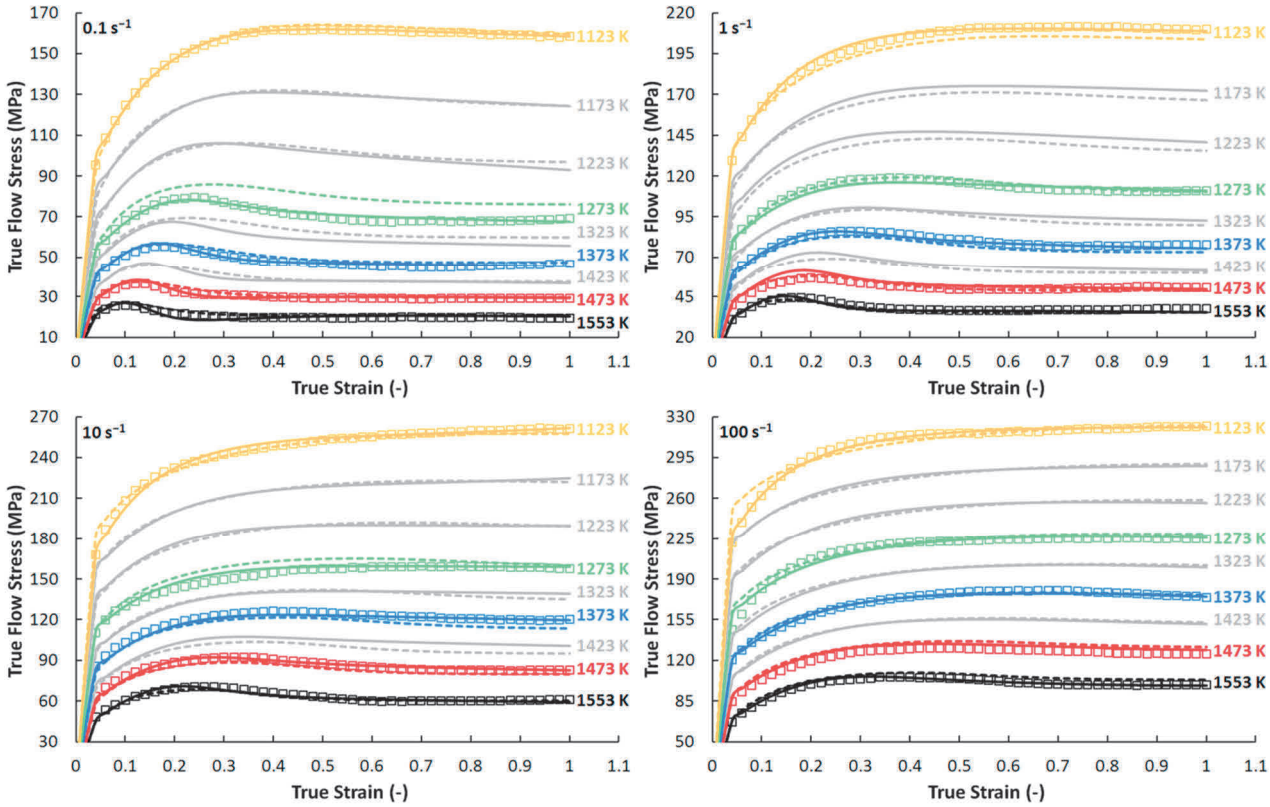

Figure 4 Flow curves of the manganese-vanadium steel: experiment (boxes), calculated by the ANN (full lines), calculated by the flow stress models with GA optimization (dashed lines)

In order to quantify the description accuracy, the relative percentage error, η (%), has been employed to compare deviations between the experimental and computed data [20]:

$$\eta_i = \frac{y(x_i) - y_i}{y_i} \cdot 100 \quad (5)$$

The η_i (%) is the *i*-th deviation (where $i = [1, n] \subset \mathbb{N}$; *n* is the number of flow curve datapoints). The y_i (MPa) and $y(x_i)$ (MPa) correspond to the *i*-th experimental and calculated flow stress value, respectively. The η-values distribution is graphically expressed in the form of histograms in **Figure 5**, where the column heights indicate the relative frequency of the η-deviation occurrence. It is clear, the η-deviation of the ANN approach is ranging in the narrower range (practically between − 8 % and 8 %) in comparison to the flow-stress-models/GA approach (ranging from − 8 % to 16 %). The mean value, μ (%), and standard deviation, σ (%), were subsequently introduced to augment the statistical evaluation [20]:

$$\mu = \frac{1}{n} \cdot \sum_{i=1}^{n} \eta_i \quad (6)$$

$$\sigma = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} (\eta_i - \mu)^2} \quad (7)$$

The μ-values and σ-values are displayed in **Figure 5**. In the case of the ANN approach, these values are closer to zero - this fact thus clearly demonstrates a higher curve fit of this method. The ANN approach is not limited by a fixed mathematical structure unlike the classic predictive models; so theoretically, the ANNs should be able to describe any approximation task.

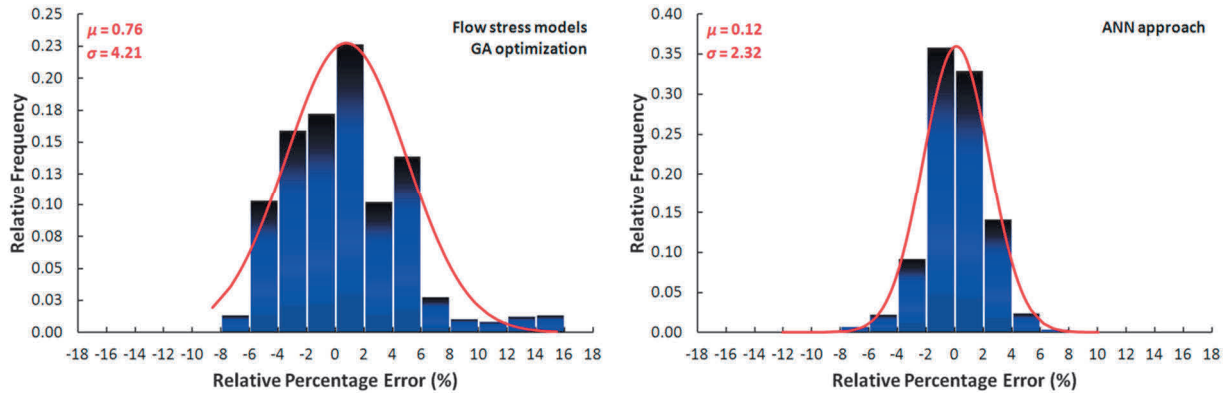

Figure 5 Distribution of the relative percentage error

5. CONCLUSION

Two different biology-inspired algorithms were utilized to approximate the experimental hot flow curve dataset of the micro-alloyed manganese-vanadium steel. In the first case, the well-known Cingara & McQueen's model and its modification were used to describe the examined flow curve dataset. A bio-inspired technique, namely genetic algorithm optimization was employed to calculate the material constants of these models. In the second case, the flow curve dataset was approximated via a multi-layer feed-forward artificial neural network with the back-propagation learning algorithm. The purpose of this research was to compare the proposed approximation methods in the sense of accuracy of hot flow curve description. Obtained results have indicated higher approximation accuracy in the case of the assembled artificial neural network. Nevertheless, the proposed flow stress models with a genetic algorithm optimization also give a good description.

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