Increasing mechanical properties of AA6082 by optimizing chemical compositions and processing parameters during extrusion

M. Terčelj[1], M. Fazarinc[1], G. Kugler[1] and I. Perus[1]

[1]Faculty of Natural Science and Engineering, University of Ljubljana, Askerceva cesta 12, 1000 Ljubljana, Slovenia

Keywords: AA6082, mechanical properties, chemical composition, processing parameters, neural network.

Abstract

AA6082 aluminum alloy is used as constructional material for highly loaded automotive parts thus increasing of yield stress and ductility is of a great importance. Database of mechanical properties, processing parameters and chemical compositions for hot extruded profiles of the alloy was obtained. A CAE neural networks individual and spatial analyses was performed to determine the influences of processing parameters and alloying elements, e.g. Mg, Si, Mn, Fe, and Cu, on mechanical properties. The results of the analyses revealed a new understanding of their influences, and the possibility of increasing the mechanical properties if processing parameters and correlations between chemical elements were closer to the optimum values. Optimization was carried out in order to increase yield stress and elongation simultaneously. In practice, the obtained values for mechanical properties have confirmed the optimized values of influential parameters as correct.

Introduction

Mechanical properties of extruded aluminum alloys are closely related to content of alloying elements and applied processing parameters, i.e. casting, homogenization, heating, extrusion, heat treatments, etc. The processing parameters and chemical composition influence final mechanical properties in a complex way. For each individual application many properties are important and the alloy development must be focused on maximizing one or a combination of multiple properties at the same time, while fulfilling minimum requirements for other properties. Thus increasing of one group of properties usually leads to a decrease of others.

The majority of investigations on the influence of chemical composition and process parameters on mechanical properties of various aluminum grades carried so far were manly based on laboratory tests and were limited to studying the influence of an individual alloying element or process parameter [1-3]. Studies involving influences of several alloying elements are rare [4]. Since the quantity of mentioned laboratory data base is usually small, the obtained results are usually not accurate enough at revealing the complex relationship between a large number of influential parameters on mechanical properties. This led us to carry out investigations in industrial environment where large enough data base can be collected. From industrial practice it is well known that small variations of the Al alloy's chemical composition and processing parameters in allowed tolerance has considerable influence on the variability of obtained final mechanical properties. With the development of artificial intelligence (e.g. neural networks) it became possible to find complex spatial influences referring to mechanical, chemical and physical problems of metal alloys.

AA6082 is mainly used for highly loaded constructional automotive parts. In order to fulfill constant demand of world market on increasing the mechanical properties, the real industrial data base was employed. To increase different mechanical properties (individually and/or simultaneously) spatial analyze of relationships between all the relevant parameters was carried out In this paper the CAE NN (Conditional Average Estimator Neural Network) analysis of influence of the chemical composition and process parameters on the yield strength and elongation of hot extruded AA6082 aluminum alloy is presented. In order to increase yield stress on one hand and to keep elongation on highest level as possible, optimization of relevant processing parameters and chemical composition was carried out.

Experimental

Hot extrusion of AA6082 was carried out on an industrial press in Impol, l.t.d., at various ram speeds, extrusion ratios and in different mult-strand configurations and at constant variation of chemical composition, simultaneously. All other parameters were constant since, based on experiences, these were previously recognized to be appropriate for achieving good final mechanical properties of extruded profiles. Thus casting was carried out at 720 °C, homogenization at 560 °C, and the billets were preheated to 500 °C before the extrusion.

The database of extruded AA6082 alloy that was formed consisted of chemical compositions, processing parameters (ram speed, extrusion ratio, casting speed, temperature, etc.) and obtained mechanical properties (yield stress, tensile strength and elongation). After several months of industrial observations in, 3968 samples or model vectors that describe the hot extrusion phenomenon were obtained. Using this data it was possible to gather a large database of the mentioned parameters that adequately covers the entire problem space essential for revealing the complex relationships between influential parameters and mechanical properties.

The average chemical composition and the range of allowable variation of studied AA6082 aluminum alloy is given in Table 1. From the table it is visible that Mg and Si as most influential alloying elements can vary in the range between 0.66 and 0.90 % and 0.80 - 1.24 %, respectively. Extrusion ratio of the extruded profiles was in the range of 2.5 - 26.6, while ram speed was in the range of 5.3 - 23.7 mm/s.

Table 1: Ranges of allowable variation of chemical composition of AA6082 aluminum alloy.

	Fe	Si	Mn	Mg	Cu	Cr
Min	0.220	.800	.400	.660	.020	.010
Max	0.440	1.240	.590	.900	.100	.170
Mean	0.315	.891	.469	.746	.058	.037
Mean -StDev	0.272	.835	.441	.702	.041	.014
Mean +StDev	0.357	.947	.497	.791	.075	.060

	Extrusion ratio	**Ram speed**	**Elongation**
Min	2.50	5.30	7.20
Max	26.60	23.70	17.39
Mean	9.10	15.47	11.97
mean-StDev	4.06	9.27	10.43
mean+ StDev	14.14	21.68	13.50

CAE NN was applied to identify the spatial influences of influential parameters. By using this method it is possible to reveal unknown relationships between them. Such an approach also has important industrial advantage since the obtained results can be relatively simply transfered to the production process.

The basics of modeling the hot extrusion phenomenon using a CAE neural network

A prerequisite for the effective spatial analysis of the influential parameters on mechanical properties of AA6082 aluminum alloy is choosing the right method. In the present case the CAE NN was used [5], which makes modeling of the mutual interactions of particular chemical elements and processing parameters possible relatively simple.

The hot extrusion (expressed in terms of the yield stress σ_y, tensile strength σ_T and elongation δ) of AA6082 aluminum alloy is determined by observing N samples during the process. The mathematical description of the observation of one sample during the hot extrusion test is called a model vector. As a result, the whole phenomenon can be described by a finite set of model vectors. Further it is assumed that each observation of one particular sample can be described by a number of variables, which are treated as components of a model vector $\mathbf{X}$ which can be further composed of two truncated vectors $\mathbf{B}$ (input parameters, e.g. chemical composition, extrusion ratio, etc.) and $\mathbf{C}$ (σ_y, σ_T and δ). Vector $\mathbf{B}$ is complementary to vector $\mathbf{C}$ and therefore their concatenation yields the complete data model, vector $\mathbf{X}$. The problem now is how an unknown complementary vector $\hat{\mathbf{C}}$ can be estimated from a given truncated vector $\mathbf{B}$ and the model vectors $\{\mathbf{X}_1, ..., \mathbf{X}_n, ..., \mathbf{X}_N\}$, i.e., how the elongation δ can be estimated from known input parameters and the available data in the database. By using the conditional probability density function [6], the optimal estimator for the given problem can be expressed as

$$\hat{\delta}_k = \sum_{n=1}^{N} A_n \cdot \delta_{nk}, \quad A_n = \frac{a_n}{\sum_{i=1}^{N} a_i} \quad \text{and}$$

$$a_n = \frac{1}{(2\pi)^{D/2} w^D} \exp\left[-\sum_{l=1}^{D} \frac{(b_l - b_{nl})^2}{2w^2}\right] \tag{1}$$

where $\hat{\delta}_k$ is the estimate of the k-th output variable (i.e. elongation), δ_{nk} is the same output variable corresponding to the n-th model vector in the database, N is the number of model vectors in the database, b_{nl} is the l-th input variable of the n-th model vector in the database (e.g., b_{n1}, b_{n2}, b_{n3}, ..., b_{nL}), and b_l is the l-th input variable corresponding to the prediction vector. D is the number of input variables, and defines the dimension of the sample space. Note that Equation (1) requires the input parameters to be normalized, generally in the range from 0 to 1, if we want to use the same width w of the Gaussian function for all of the input variables.

The Gaussian function is used for a smooth interpolation between the points of the model vectors. In this context the width w is called the "smoothing" parameter. The selection of a proper value of w is discussed elsewhere [7].

An intermediate result in the computational process is the estimated probability density function, $\hat{\rho}$, of the known input variables

$$\hat{\rho} = \frac{1}{N}\sum_{n=1}^{N} a_n \tag{2}$$

The CAE approach requires an appropriate database and a numerical analysis for each estimate. There are no fixed functional relations between the input and output parameters. Any number of input parameters (which are contained in the database) can be used, and different databases or different subsets of a database can be employed. It should be noted that when traditional BP (back-propagation) neural networks are compared with the CAE neural network, the so-called "learning" is replaced by determining the appropriate values of the smoothing parameter in Equation (1). They are determined by a "trial-and-error" procedure with the "leave-one-out cross-validation method". The average prediction error can be defined as a kind of RMSE error [8] in a similar way as in traditional BP NN learning procedures.

Results and discussion

As it is presented in Figure 1 there is a high correlation between tensile strength and yield stress on one side and no correlation between tensile strength and elongation. Thus as output parameters yield stress and elongation were selected. Value of 0.15 for smoothness parameter w was obtained as optimal and was applied in all analyses.

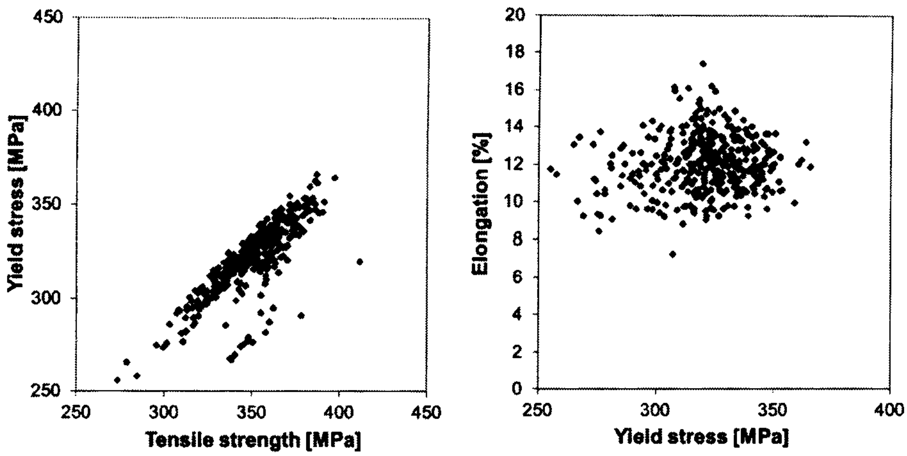

Figure 1: The correlation between output parameters, yield stress and tensile strength (left), elongation and yield stress (right).

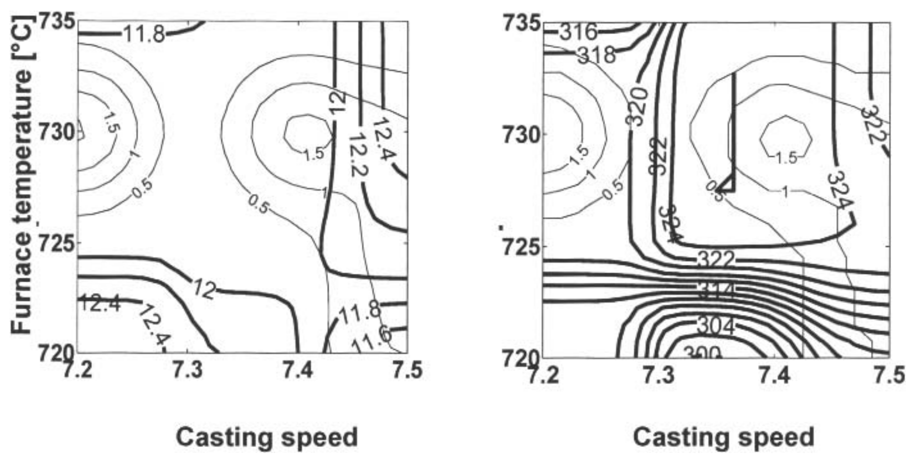

Figure 2: The influence of furnace temperature and casting speed on elongation (left) and yield stress (right).

Influence of process parameters on mechanical properties

In the first steep of the analyze the influence of most important process parameters like casting speed, casting temperature, ram speed, extrusion ratio and the number of extruding strands has been carried out. In all figures the dependence of two parameters on selected mechanical property is presented. Thin isolines present the density of data in this area (Eq. 2). Higher densities of isolines mean higher density of data. The thicker lines represent the values of individual output parameter, i.e. yield stress and elongation.

In Figure 2 the influence of furnace temperature and casting speed on selected mechanical properties are presented. Highest values for elongation and yield stress were obtained at casting speed in the range of 7.3 – 7.5 mm/s and at furnace temperature over 725 °C. Analysis of influence of casting temperature, temperature in the runner bar and casting speed reveals that the highest values for mentioned mechanical properties can be obtained at casting speed above 7.4 mm/s, furnace temperature of about 730 °C and temperature in the runner bar of 720 °C.

In Figure 3 the influence of ram speed and extrusion ratio on elongation and yield stress are presented, respectively. With increasing extrusion ratio and decreasing ram speed higher values for elongation can be obtained while the highest value for yield strength can be obtained at the extrusion ratio of 15 and the ram speed of 15 mm/s.

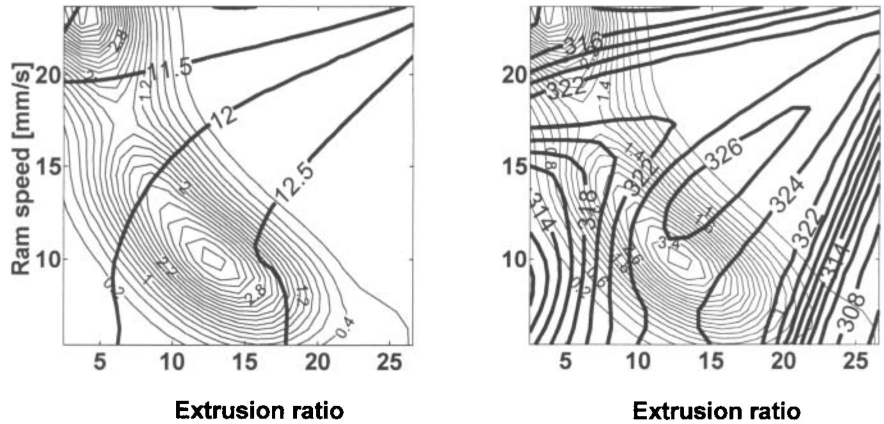

Figure 3: The influence of ram speed and extrusion ratio on elongation (left) and yield stress (right).

The influence of chemical composition on mechanical properties

In this part of analysis the influence of chemical composition on the mechanical properties of the alloy was studied. First the influence of each major chemical element and then the most important pairs of chemical elements were analyzed. In all graphs the thin (red) line represents the data density (higher density means more input vectors in this section), while thick (black) line represents the mechanical properties. Only selected results are shown in Figure 4. In general, higher Si and Mn values increase, while higher Cu values decrease the elongation. Influence of Mg is minor. Please note that influences are reliable only for higher ρ values.

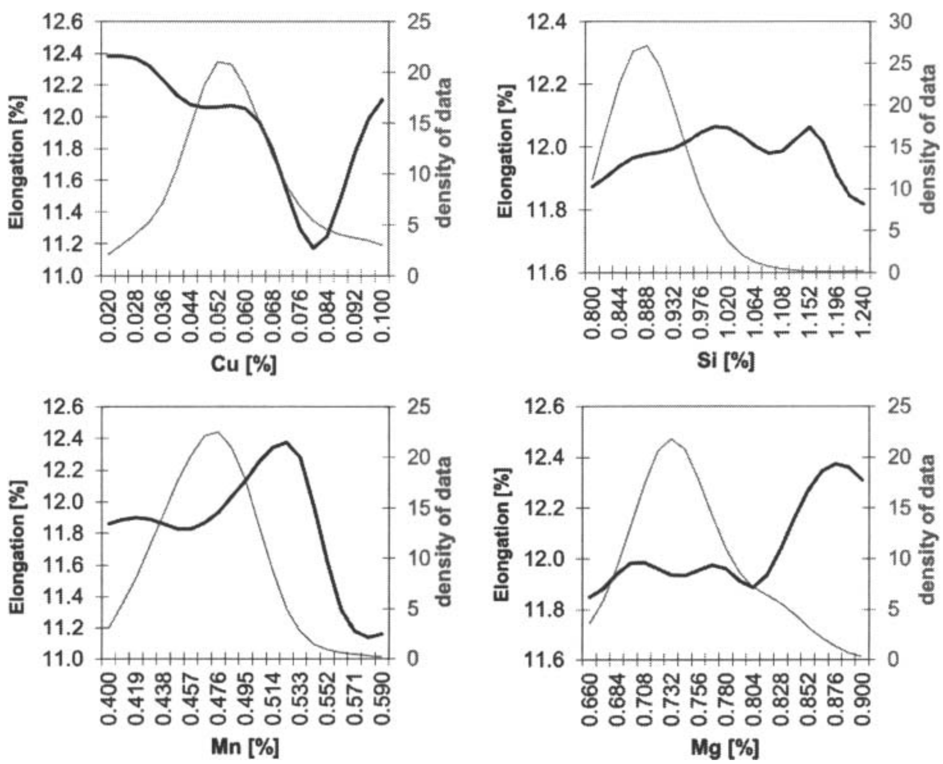

Figure 4: The influence of selected chemical elements on elongation.

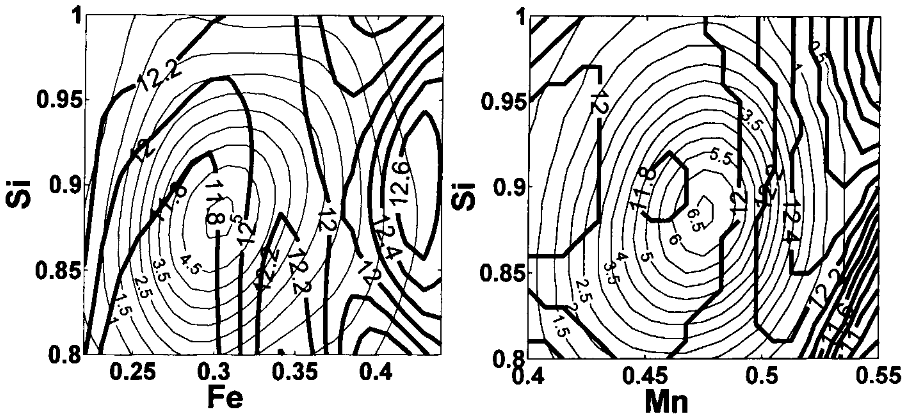

Figure 5: **The** simultaneous influence of Fe and Si (left), and Mn and Si (right) on elongation

In Figure 5 the simultaneous influence of Fe and Si and Mn and Si on the elongation are shown. It turns out that the highest elongation appears at higher values of Si and 0.3 % of Fe (note that at higher values of Fe grater values of elongation can be observed, however, due to the small ρ values such results are unreliable). In the study of the simultaneous influence of Mn and Si the highest elongation can be obtained at 0.5 % of Mn.

Optimization

Standard optimization was not being carried out because of unreliability of all technological parameters and uncertainty of ensuring the predetermined chemical composition. Moreover, producer's demand within the first phase of the development was the optimization of chemical composition only. Therefore, based on the expert knowledge, six most influential chemical elements were identified, namely Fe, Si, Mn, Mg, Cu and Cr. On the base of the influence of individual as well as pairs of elements (Figures 4 and 5), fixed zones of a few chemical elements with highest mechanical properties were determined.

Analyses of simultaneous influence of all six chemical elements on yield stress and elongation were then carried out for fixed values of Fe which amounts 0.35 % and 0.42 %, of Cu at 0.05 %, of Cr at 0.03 % and of Si at 0.8, 0.9 and 1.0 %. Results of analyses reveal that the highest values of yield stress can be obtained at 0.42 % of Fe, at higher contents of Si (between 0.9 % and 1.0 %), Mn content between 0.44 % and 0.53 %, and Mg content between 0.65 % and 0.74 %. Similar conclusions may be obtained for elongation, only the relations between Mn and Mg are slightly changed; the highest values of elongation can be obtained at 0.42 % of Fe, at higher contents of Si (between 0.9 % and 1.0 %), Mn content between 0.52 % and 0.57 %, and Mg content between 0.65 % and 0.74 % (Figure 8).

It should be emphasized, that we were looking for a compromise solution for optimization of chemical composition. Namely, we were searching for partial (i.e. smaller) improvement of both mechanical characteristics (yield stress **and** elongation) at the same time on the expense of larger individual improvement of any of the two mechanical characteristics (yield stress **or** elongation). Usually the important improvement of one characteristic is achieved on the expense of the aggravation of the second (e.g. increase of Cu content up to 0.6 % increases yield stress and decreases elongation).

Based on the results from CAE parametric analyses, use of linear regression gives the equation that determines the largest yield stress and elongation, depending on the content of individual alloying element. Equations can be used within the ranges of individual chemical elements, as presented in Table 2.

$$\begin{aligned} R_{p02}[MPa] = {} & 328.53 + 53.46 \cdot \%Fe + \\ & + 12.18 \cdot \%Si + 26.25 \cdot \%Mn \\ & - 77.12 \cdot \%Mg + 126.37 \cdot \%Cu \\ & - 11.64 \cdot \%Cr \end{aligned} \tag{3}$$

$$\begin{aligned} E[\%] = {} & 12.37 + 1.21 \cdot \%Fe - 5.45 \cdot \%Si \\ & + 6.75 \cdot \%Mn + 3.6 \cdot \%Mg \\ & - 18.15 \cdot \%Cu - 0.62 \cdot \%Cr \end{aligned} \tag{4}$$

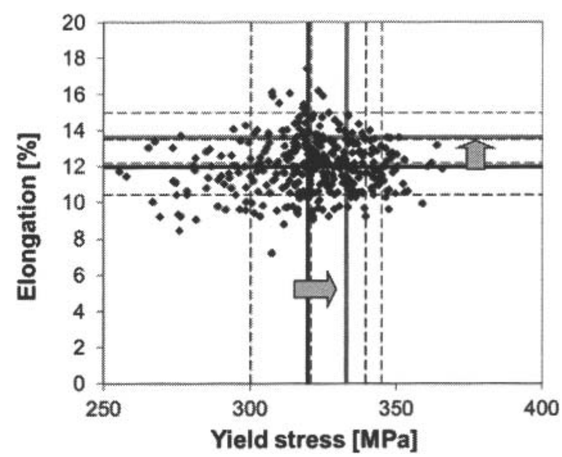

Figure 6: Optimization: average increase of yield stress for about 13 MPa (320 MPa to 333 MPa) and average increase of elongation for about 1.6 % (12 % to 13.6 %).

Table 2: Allowable ranges of individual chemical elements for the use in Eqs. 3 and 4 (wt. %).

	Fe	Si	Mn	Mg	Cu	Cr
Max %	0.47	1.02	0.50	0.72	0.07	0.05
Min %	0.37	0.88	0.44	0.62	0.03	0.01

Conservative assessment for optimal expected values amounts to 333 MPa and 13.6 % for yield stress and elongation, respectively. Expected standard error amounts to 12 MPa for yield stress and 1.4 % for elongation (Figure 6).

Test alloy

Based on optimization, job order with determined chemical composition for maximum yield stress was made. As expected, due to the nature of production process, it was impossible to assure that the determined and actual chemical composition would be the same. Actual and determined chemical compositions are presented in Table 3.

Table 3: Determined and actual chemical composition of test alloy (wt. %).

	Fe	Si	Mn	Mg	Cu	Cr
Determined	0.37	1.02	0.50	0.62	0.07	0.03
Actual	0.34	1.05	0.51	0.64	0.06	0.05

With the use of equations 3 and 4 yield stress and elongation, that amount to 330 MPa and 11.6 % were calculated, respectively. Actual average measured values were 333.5 MPa for yield stress and 12.0 % for elongation. In Figure 7 the predicted results and actual measurement are presented, together with the predicted cumulative distribution function. Differences between actual and predicted values (individual, mean, median, fractals) are small and within the expected accuracy. For example, the difference between mean values amount to 1 % and -3.4 % for yield stress and elongation, respectively.

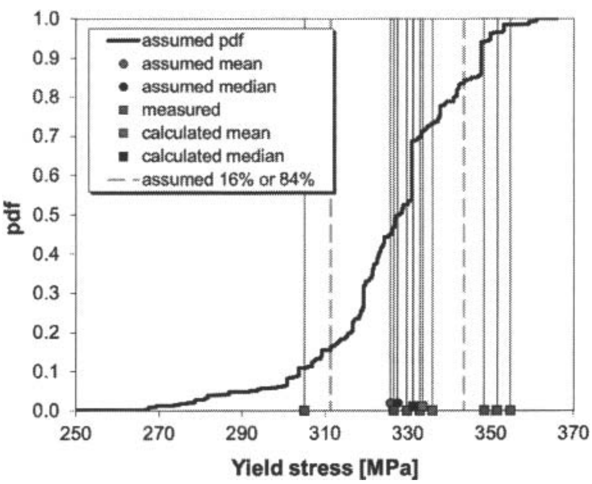

Figure 7: Examples of the test alloys and their statistical distribution for yield stress. Calculated (actual) mean is slightly above the predicted mean yield stress (330 MPa).

Conclusions

The CAE neural network was proposed for modeling the influence of different chemical and technological parameters on the mechanical properties of the 6082 alloys during the hot extrusion. Analyses reveal the areas of influential parameters with positive influence on obtained mechanical properties as well as the areas that should be avoided.

Analyses indicate that the highest (»peak«) values for elongation and yield stress do not coincide. The optimal values for elongation and yield stress therefore cannot be obtained at the same values of ram speed and extrusion ratio, and chemical composition. We were searching for partial (i.e. smaller) improvement of both mechanical characteristics (yield stress and elongation) at the same time on the expense of larger individual improvement of any of the two mechanical characteristics. Usually the important improvement of one characteristic is achieved on the expense of the aggravation of the second.

Test alloy revealed that the optimization was successful. In general, expected increase in yield stress would amount to 4% and in elongation to 13%.

References

[1] S.H. Hsiang, Y.W. Lin, J Mater Process Technol, 192-193, (2007), 292-299.

[2] S. Norasethasopon, J Mater Process Technol 203(1-3), (2008), 137-146.

[3] T. Tryland, O.S. Hopperstad, M. Langseth, Materials and Design, 21(5), (2000), 477-492.

[4] Z. Jančíková, V. Roubíček, D. Juchelková, Metalurgy, 47(4), (2009), 339-342.

[5] T. Vecko-Pirtovsek, I. Perus, G. Kugler, M. Tercelj, ISIJ International, 49(3), (2009), 395–401.

[6] I. Grabec, W. Sachse, Synergetics of Measurement, Prediction and Control, ISBN 3-540-57048-9, Springer-Verlag, 1997.

[7] I. Perus, P. Fajfar, Earthquake Eng Struct Dyn, 39(12), (2010), 1395-1416.

[8] M. Terčelj, I. Perus, R. Turk, Tribology International, 36, (2003), 573-583.