MODELLING THE EFFECT OF ALLOY ELEMENTS IN THE HOT STRENGTH OF STEEL[1]

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Abstract

The information about the quantitative effects of alloy elements on the hot strength of steels is scarce and contradictory. Its effects can change according to alloy content and specific conditions of the hot forming process, as they can activate different hardening or softening mechanisms. Three empirical approaches were initially adopted in this work to rank and model hot strength in steels in function of their chemical composition: activation energy of deformation Q, mean hot flow stress and parameters of the Hajduk equation. Both alloy elements effect and steel ranking regarding to hot strength varied according to the selected parameter. Besides that, no simple and precise model could be developed from these parameters. This fact led to the development of a neural network with this purpose; its input parameters were C, Mn, Si, Al, Cr, Cu, Nb, V, Ti and N contents, as well strain temperature, degree and strain rate. This new approach showed better precision than the former trials, making easy to forecast the hot strength behavior of new steel alloys. This solution proved to be simple and very efficient, minimizing the development time of a mathematical model for this purpose.

Introduction

The mathematical modelling of hot strength from strain temperature, degree and rate was and still remains exhaustively being studied for several kinds of steel; in fact, many equations were proposed [1]. This may be due to the remarkable influence of the forming parameters on hot strength, specially temperature [2]. However, knowledge about the effect of alloy elements on hot strength still is scarce and contradictory.

For example, the effect of carbon on hot strength depends significantly on forming conditions. For low values of strain degree, this interstitial element increases the drag tension needed for the migration of dislocations, due to the formation of carbon atmospheres and excess vacancies, raising strain hardening. However, as strain degree increases, this element promotes dynamic recrystallization, as it increases the diffusivity of vacancies. This decreases strain hardening and, in consequence, the magnitude of hot strength. Such phenomena can explain the contradictory relationship between carbon content and activation energy for hot deformation Q observed in several papers [3,4,5]

Another interstitial element frequently present in steels, nitrogen, normally shows a narrow content range. So, its influence generally is not great [2]. However, in Ti microalloyed steels, the presence of this element can promote the precipitation of TiN, refining the initial austenitic grain size and thus leading to an indirect increase of hot strength up to 20%. This is particularly noticeable when steel is reheated to high temperatures before hot forming [6].

The hardening effect derived from solid solutions of substitutional elements fundamentally depends on the difference between the atomic diameters of the element and iron [2]. So, the hardening effect decreases according to the following sequence: niobium, titanium, vanadium, molybdenum, silicon, manganese and chrome. This effect is greater than expected when there is a combination of elements in the alloy, due to synergic effects [7].

However, Nb can promote a considerable increase in hot strength due to the supression of austenite recrystallization during forming below the so-called temperature of no-recrystallization (T_{nr}) [2]. Cu has a similar effect, but its influence is weaker than Nb [8].

Some authors tried to verify the effect of the carbon equivalent (C_{eq}) parameter on hot strength, but no precise correlation was achieved [9,10].

The influence of alloy elements on Ar_3 also influences the magnitude of hot strength. It is well known that hot strength increases as temperature decreases, but, in the vicinity of Ar_3, it momentarily decreases, as ferrite is softer than austenite at the same temperature. This local decrease, however, is less pronounced in steels with higher Mn, as this element reduces the kinetics of the ferrite transformation [2,11].

The influence of alloy elements on the hot deformation activation energy **Q** is not always clear, due to the differences in the experimental methodology observed in the literature. Roughly speaking, the increase of Mn and Nb tends to raise the magnitude of **Q** [12,13]. The presence of different alloy elements in the industrial alloys studied in the literature makes difficult the determination of the real effect of specific elements on **Q**.

The precision of equations for the calculation of hot strength from chemical composition is lower than mathematical models developed for specific alloys [1]. The first equation that included the effects of chemical composition on hot strength was developed by Ekelund, which included the contents of C, Mn and Cr as parameters. Another classical model is the equation of Misaka; its first version only considered the effect of C in hot strength; a second version included the influence of Mn, V, Mo and Ni, besides the effect of the transformation of austenite in ferrite. This last effect was also considered in the model of Shida which, for its turn, only considered the effect of C among the alloy elements [2].

The Hajduk equation [14],

$$\sigma = \sigma_0 \, e^{-a\,T} \, \varepsilon^b \, \dot{\varepsilon}^c$$

does not contain terms with interactions between the independent variables - strain temperature, degree and rate -, thus avoiding multicollinearity effects that could affect its physical consistency. So, there is some hope about a correlation between the magnitude of the constants σ_0, **a**, **b** and **c** of this equation and alloy content. Some authors determined the value of these constants for dozens or even hundreds of different ferrous and non-ferrous alloys [1,14], but did not try to develop such correlation.

The lack of data and reliable mathematical models which account for the influence of alloy elements on hot strength motivated the development of a research work for this purpose, specifically for the low carbon and microalloyed steels processed at the Plate Mill of Companhia Siderúrgica Paulista - COSIPA. Besides the development of such mathematical model, one additional objective of this work was to rank the hot strength of these steels, in order to assess its "rollability".

Experimental Procedure

The hot strength of the most frequently processed steels at COSIPA plate mill was determined through isothermal torsion tests performed at the Federal University of São Carlos, Brazil. Nine steels were studied; three of them were low carbon steels, whereas six alloys were microalloyed. Their chemical compositions can be seen at Table I.

Steel samples, cut from plates, were previously austenitized at 1100°C during ten minutes. A misture of argon and hydrogen was used as a protective atmosphere. After that, they were cooled until they reach the test temperature. At this moment, deformation was applied in the specimen, up to a strain degree of 2,0. The tests were carried out under temperatures of 1100, 1000, 900 and 800°C, and strain rates of 0.5, 1.0 and 5.0 s^{-1}.

Data got from these tests was processed in order to develop a relationship between chemical composition and hot strength. The following parameters were calculated: activation energy of hot deformation **Q,** according to the procedure of UVIRA & JONAS [15]; hot mean flow stress, considering all forming conditions; and the constants σ_o, **a**, **b** and **c** of the equation of Hajduk. The effect of alloy elements over these parameters was statistically determined, through the Pearson matrix, stepwise multiple correlation and multiple principal components analysis, using the *Systat* software.

AÇO	C	Mn	Si	Al	Cr	Cu	Nb	V	Ti	N
C1	0,09	0,53	0,18	0,029	-	-	-	-	-	0,0047
C2	0,15	0,90	0,21	0,039	-	-	-	-	-	0,0053
CMn	0,16	1,48	0,36	0,039	-	-	-	-	-	0,0048
Nb	0,18	1,34	0,30	0,025	-	-	0,033	-	-	0,0074
NbTi1	0,14	1,11	0,30	0,044	-	-	0,020	-	0,015	0,0054
NbTi2	0,14	1,34	0,23	0,035	-	-	0,033	-	0,014	0,0048
NbTiV	0,12	1,50	0,31	0,038	-	-	0,047	0,051	0,020	0,0064
NbCrCu1	0,16	1,03	0,41	0,029	0,54	0,23	0,025	-	-	0,0107
NbCrCu2	0,13	0,99	0,38	0,042	0,50	0,22	0,014	-	-	0,0095

Table I: Chemical compositions of steels studied in this work.

Finally, a neural network for the prediction of hot strength from chemical composition of steels and hot forming parameters was developed. This perceptron had 13 neurons in the input layer (strain temperature, degree and rate; carbon, manganese, silicon, aluminium, copper, chromium, niobium, titanium, vanadium and nitrogen contents). The total number of neurons in the hidden layers was 27, making an analogy with the theorem of Hecht-Kolmogorov [16]; they were uniformly distributed in three hidden layers, each one with 9 neurons. The output layer, obviously, had only one neuron, with the predicted value of hot strength. The process of conception, training and test of this neural network was carried out using the *NeuralWorks* software. The training step of the neural network was made using 80% of the available data; the remaining 20% was reserved to test its performance.

Experimental Results and Discussion

The values of **Q** calculated for the steels studied in this work can be seen in Figure 1. They are within the range of values typical for low carbon and microalloyed steels, even though the value corresponding to the Nb steel was somewhat higher. The statistical analysis showed that **Q** is significantly influenced by the C and Mn contents. The respective Pearson correlation coefficients were 0,760 and 0,518. The positive correlation between C and **Q** was unexpected, according to the literature [5]. However, there is some positive correlation between this element and other alloy elements in the steels studied in this work; in fact, the correlation coefficient between C and Mn contents is 0,503. Hence, the effect of C over the values of **Q** detected in this work can not be considered as being due exclusively to this element.

For its turn, the values of hot mean flow stress - shown in Figure 2 - showed some correlation with the Nb and C_{eq} contents of steel, with Pearson correlation coefficients of 0,504 and 0,693, respectively. This later correlation is not confirmed by the literature [9], but it is insufficient to be used as a good prediction model for hot strength in function of the chemical composition of steel.
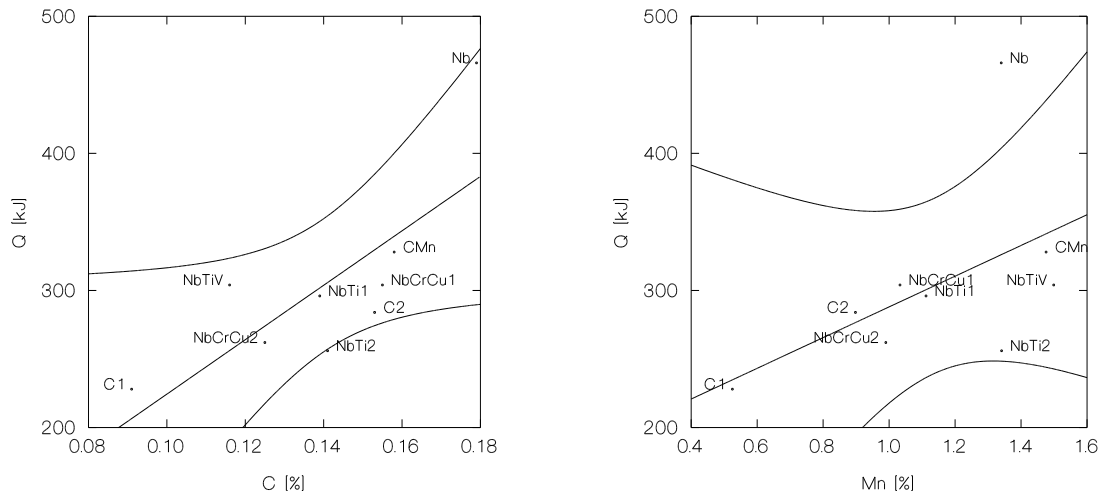

Figure 1: Relationship between the calculated values of **Q** for the steels studied in this work and its C and Mn contents.
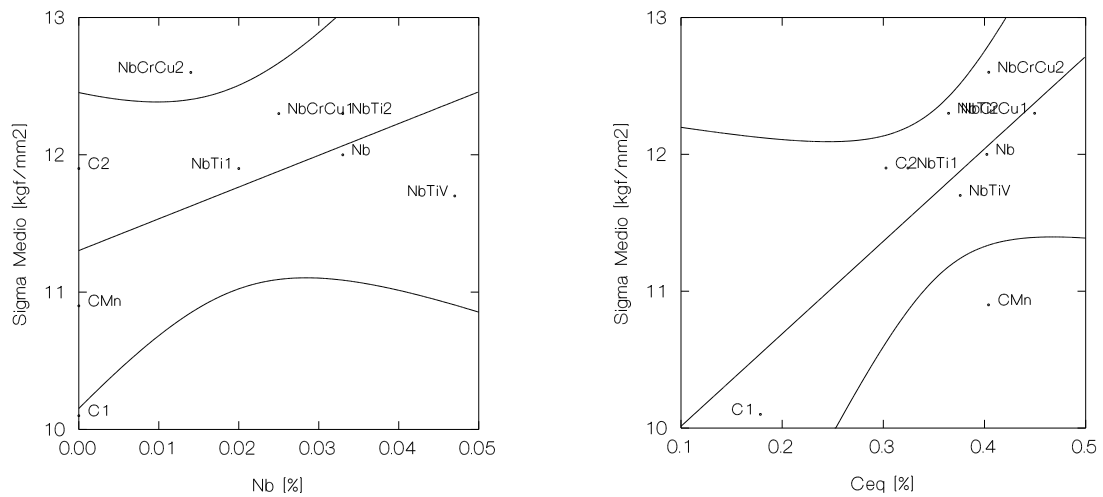

Figure 2: Relationship between the hot mean flow stress for the steels studied in this work and its Nb and C_{eq} contents.

The correlations between **Q** and the hot mean flow stress with chemical composition were different. So, ranking steels according to these two parameters will lead to different

results. It should be noted, however, the value of **Q** is determined only from the peak value of hot strength and strain rate available for each test, while the hot mean flow stress is calculated from a broader range of values from the curve stress versus train. This fact renders this last parameter less prone to experimental errors, as it is determined from a significantly greater number of data records.

The statistical analysis of the effect of alloy elements in the parameters of the Hajduk equation showed that C once more was the most influencing element, specially over σ_o (r=0.714) and **a** (r=0.762), and with some effect over **b** (r=-0.592) and **c** (r=-0.564), as shown in Figure 3. This finding is confirmed by the literature: the increase of C content leads to higher values of basic hot strength and enhance the temperature effect on hot strength, but reduce the effect of strain degree and strain rate [4]. It was also verified that Mn, Si and Nb also reduce the effect of strain rate on hot strength, with Pearson correlation coefficients of -0.636, -0.580 and -0.542, respectively.
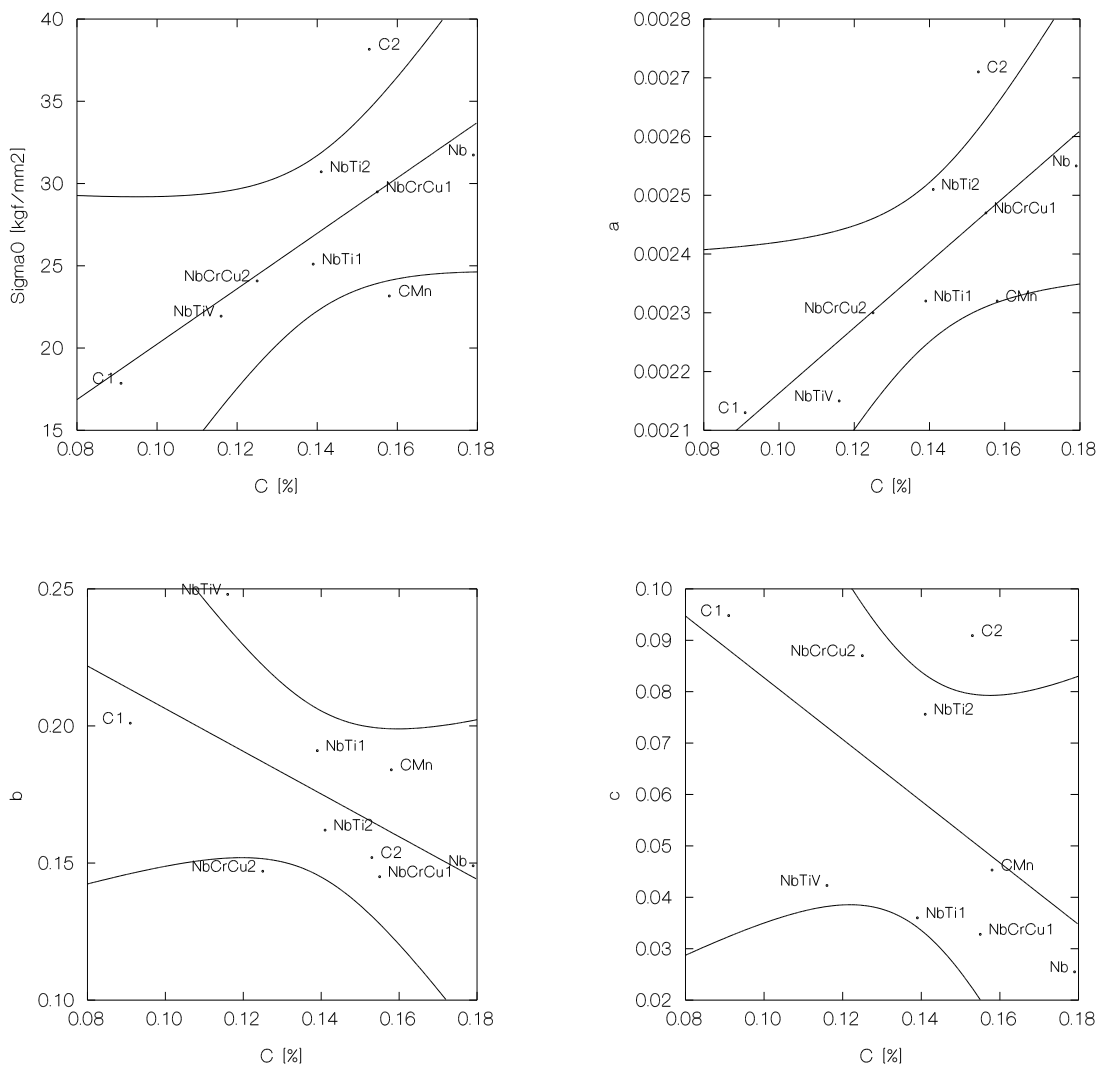

Figure 3: Effect of C on the parameters of the Hajduk equation.

Table II shows the performance of linear equations developed using stepwise multiple correlation between the parameters of Hajduk equation and the chemical composition of the steels. Very good results were got regarding the prediction of basic hot strength (σ_o) and the constant of the exponential function of the temperature (**a**); a reasonable relation was also achieved for the exponent of the strain degree (**b**). However, results got for strain degree were not statistically significant. This prevented the use of this approach for the development of a precise prediction model for hot strength from the chemical composition and parameters of the hot forming process.

	ELEMENTS	r	STANDARD ERROR	CONFIDENCE [%]
σ_o	C(+), Si(-), Cu(+), V(+), Al(+)	0,994	0,781	99,8
a	C(+), Si(-), Cu(+), Al(+), V(+)	0,993	0,001	99,8
b	V(+), C_{eq}(-)	0,803	0,018	99,2
c	Mn(-)	0,404	0,066	*93,4*

Table II: Performance summary of the linear equations developed from stepwise analysis between the parameters of the Hajduk equation and the chemical composition of the steels. The alloy elements were ranked inversely to its significance in the equations.

The failure of the development of a model for the prediction of hot strength from chemical composition and hot forming parameters from the values of **Q**, hot mean flow stress and parameters of Hajduk equation paved the way for the application of neural networks in this problem. There are already some examples of this application in the literature [10].

The neural network developed in this work allowed the prediction of hot strength from the C, Mn, Si, Al, Cr, Cu, Nb, V, Ti and N contents of steel, as well its hot forming parameters (strain temperature, degree and rate). After testing with 20% of the available data, not "shown" to the perceptron during its training step, this model revealed a very good performance: Pearson correlation coefficient of 0,939 and a standard error of 11,8 MPa. This precision is inferior to the performance of hot strength models developed for specific alloys [1], but is very good for a model including chemical composition. This trained neural network was converted in a simple BASIC subroutine for use in mathematical models for off-line calculation of hot rolling load and pass schedule for the COSIPA plate mill.

A neural network is as good as the data used during its training step. The alloys studied in this work were selected according to its participation in the productive mix of the plate mill. Unfortunately, this criterion was not adequate from a scientific standpoint. For example, as told before, Mn content of the alloys used in this paper tended to be proportional to C content. So, the neural network developed in this work probably will not yield results so precise for steels with high C and low Mn contents, for example, as the neural network did not "learn" about this specific kind of alloy. This situation only can be corrected adding more hot strength information to its training data set. So, further hot torsion tests must be carried out, preferably using judicious experiment planning, in order to refine this model.

Conclusions

The main objective of this work was to rank steels processed in a plate mill according to its hot strength and to develop a model to predict this property from steel chemical composition and hot forming parameters. The conclusions derived from this development are as follows:

- C and Mn were the elements with maximum influence on the activation energy for hot deformation **Q**. However, the real effect of C was masked by Mn, as its contents were proportional to each other;

- For its turn, Nb and C_{eq} contents were the most influencing chemical composition parameters over the hot mean flow stress;

- Steel ranking according **Q** or hot mean flow stress was different. The last parameter is more reliable, as its determination requires significantly more hot strength information than **Q**;

- The analysis of the influence of chemical composition on the parameters of the Hajduk equation showed that C was the most influencing element, followed by Mn, Si and Nb, that affected significantly only the exponent of strain rate. Good linear relationships were developed through stepwise regression for the parameters σ_o, **a** and **b**, but this was not true for constant **c**, that is, the exponent of strain rate.

- The most promising approach for the development of an empirical relationship for the prediction of hot strength from steel chemical composition and hot forming parameters was the development of a neural network, which showed very good performance: r = 0,939 and standard error of 11,8 MPa. However, as it was trained from data relative of only nine alloys, additional work must be developed in order to expand its range of applicability. This can be done with addition hot torsion testing of judiciously choosed new alloys or through the incorporation of data available in the literature.

Acknowledgements

References

1) SPITTEL, T. & HENSEL, A. Kraft- und Arbeitsbedarf bildsamer Formgebungsverfahren. VEB Deutscher Verlag für Grundstoffindustrie, Leipzig, 1978. 476 p.

2) TAMURA, I. e outros. Thermomechanical Processing of High Strength Low-Alloy Steels. Butterworths, London, 1988. 248 p.

3) MEAD, H.W. & BIRCHENALL, C.E. Transactions of the AIME, Oct. 1956, 1326-39.

4) SAKAI, T. & OHASHI, M. Tetsu-to-Hagané, Sept. 1981, 2000-9.

5) COLLINSON, D.C. et alii. In: MATHEMATICAL MODELLING OF STEEL ROLLING. Proceedings. The Materials Society, London, 1993, 283-95.

6) CAMEI, K. e outros. In: XLVI A.B.M. ANNUAL CONGRESS. Proceedings. Associação Brasileira de Metais, São Paulo, 1991, 471-86.

7) AKBEN, M.G. & JONAS, J.J. In: HSLA STEELS - TECHNOLOGY & APPLICATIONS. Proceedings. American Society for Metals, Metals Park, 1983, 149-161.

8) ABE, T. e outros. Transactions of the ISIJ, June 1987, 478-84.

9) MAZUR, V.L. & KHZHNYAK, D.D. Steel in the USSR, Aug. 1991, 350-2.

10) HWU, Y.J. e outros. Steel Research, Feb. 1996, 59-66.

11) KASPAR, R. e outros. Steel Research, Mai 1983, 195-8.

12) SANKAR, J. e outros. Metals Technology, Sept. 1979, 325-31.

13) LAASRAOUI, A. & JONAS, J.J. Metallurgical Transactions A, July 1991, 1545-1558.

14) HAJDUK, M. e outros. Hutn Listy, 8, 1972, 567-71 (Translation BISI 11281).

15) UVIRA, J.L. & JONAS, J.J. Transactions of the Metallurgical Society of AIME, Aug. 1968, 1619-26.

16) NIELSEN, R.H. Neurocomputing. Addison-Wesley Publishing Company, Reading, 1991. 433 p.