Modeling the Controlled Rolling Critical Temperatures Using Empirical Equations and Neural Networks[1]

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Abstract

The knowledge of the critical temperatures in controlled rolling - T_{nr}, Ar_3 and Ar_1 - is fundamental for the correct selection of the temperatures where should happen the several steps of this process. In this work these parameters were determined for the most frequently microalloyed steels processed in the Plate Mill of COSIPA. It was verified that the isolated effect of several alloy elements over these critical parameters was not very clear, fact attributed to their short magnitude range among the steels studied in this work. Nb and Si were the most statistically significant elements for the determination of T_{nr} and A_{r3}, respectively. The mathematical modeling through neural networks for the calculation of those two parameters, starting from steel chemical composition, was shown to be more precise than its calculation through the former empirical models. Their performance can be further improved through the use of larger amounts of data during the learning phase of the neural networks.

KEY WORDS: Hot Torsion Tests, No-Recrystallization Temperature, A_{r3} Temperature, Mathematical Models

1. Introduction

The correct execution of the controlled rolling of a microalloyed steel requires the knowledge of its critical temperatures, that is, the "no-recrystallization" temperatures (T_{nr} or $T_{95\%}$, and $T_{5\%}$)[1)], ferrite transformation start (A_{r3}) and finish (A_{r1}). These temperatures define the correct temperature ranges of the several phases of controlled rolling. The roughing stage must be conducted above T_{nr}; a holding stage (no rolling) must be adopted between T_{nr} and $T_{5\%}$; the finishing stage is delimited between $T_{5\%}$ and A_{r3}; intercritical rolling occurs between A_{r3} and A_{r1}; and ferrite rolling is done below A_{r1}.

There are several justificatives for the determination of that temperatures[2)]. In first place, they allow a qualitative forecast of the evolution of the rolling loads along temperature, that is to say, along the pass schedule. On the other hand, its knowledge can base the development of pass schedules that optimize the "flattening" degree of the austenite grains and/or ferrite strain hardening.

The determination of T_{nr} in laboratory was already got by several ways: through hot torsion, compression or even rolling tests[2)], as well even under industrial plate rolling conditions[3)]. The determination of Ar_3 after hot deformation can be done using dilatometers with coupled hot compression devices[4)], through thermal analysis of hot rolled samples[5)] or using a hot torsion device with a coupled dilatometer[6)]. However, the empirical method developed by Boratto et alii[2)] is particularly useful, because it allows simultaneous determination of the T_{nr}, Ar_3 and Ar_1 temperatures using only one test. Boratto's approach consists of a single hot torsion test where multiple deformation passes, applied under decreasing temperature, are applied to the specimen. The posterior analysis of the evolution of mean hot strength along the inverse of the corresponding temperature allows the determination of T_{nr}, Ar_3 and Ar_1. However, the accuracy of these calculated parameters depends on the subjective interpretation of the curve, which can produce significant variation in the final results. The same authors studied 17 microalloyed steels using this approach and proposed the following equation for the calculation of T_{nr}:

$$T_{nr} = 887 + 464\,C + (6445\,Nb - 644\sqrt{Nb}) + (732\,V - 230\sqrt{V}) + 890\,Ti + 363\,Al - 357\,Si \quad \textbf{(1)}$$

An option for the calculation of T_{nr}, with a more sound theoretical foundation, requires the use of equations that describe recrystallization and precipitation kinetics. In this approach, T_{nr} is defined as the intersection of the curves corresponding to the time necessary for the occurrence of 95% of austenite recrystallization and for the occurrence of 5% of carbonitride precipitation, as shown in Figure 1. Such model was originally developed by Dutta and Sellars[1)] and refined by other authors[7)]. The time required for 5% of precipitation can be determined by the following equation:

[1] 7th International Conference on Steel Rolling, The Iron and Steel Institute of Japan, Chiba, 1998, 629-633.

$$t_{p0,05} = \frac{200 \exp\left(\frac{-200000}{R\,T_R}\right)}{Nb\,\varepsilon\,\sqrt{Z}} \exp\left(\frac{270000}{R\,T}\right) \exp\left(\frac{2{,}5.10^{10}}{T^3\,(\ln k_s)^2}\right)$$

(2)

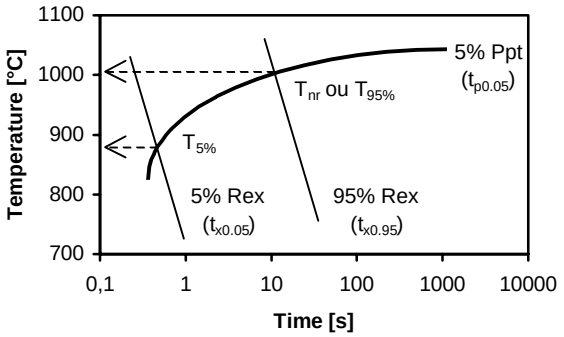

Figure 1: Interaction between austenite recrystallization and precipitation kinetic curves, showing as the different no-recrystallization temperatures (T_{nr}/$T_{95\%}$ and $T_{5\%}$) are determined.

where $\mathbf{T_R}$ is the temperature under which the material was deformed, $\boldsymbol{\varepsilon}$ is the true strain, **Z** is the Zener-Hollomon parameter, **R** is the universal gas constant, **T** the temperature and $\mathbf{k_s}$ the rate of Nb supersaturation, given by

$$k_s = \frac{[Nb]\left[C + \frac{12\,N}{14}\right]}{10^{\left(2{,}26 - \frac{6770}{T}\right)}}$$

(3)

and the time necessary for 5% recrystallization can be calculated by the formula

$$t_{x0,05} = 6{,}75.10^{-20}\; d_0^2 \exp\left(\frac{300000}{R\,T}\right) \exp\left[\left(\frac{275000}{T} - 185\right) Nb\right]$$

(4)

where $\mathbf{d_0}$ is the initial austenitic grain size of the specimen.

This method has a particular advantage: it not only allows the calculation of T_{nr}, that is, the minimum temperature at which austenite completely recrystallizes between hot rolling passes, as well it permits the calculation of $T_{5\%}$, the maximum temperature where austenite did not show any recrystallization after hot deformation, which corresponds to the intersection of $t_{p0.05}$ and $t_{x0.95}$. This last parameter can be calculated by the formula

$$t_{x0.95} = 7.66\; t_{x0.05}$$

(5)

The Ar_3 temperature values got by Boratto et al.[2] showed good fitting with the formula proposed by Ouchi et al.[5]:

$$Ar_3 = 910 - 310C - 80Mn - 20Cu - 15Cr - 80Mo + 0{,}35(h - 0{,}8)$$

(6)

where **h** is the thickness of the sample being submitted to rolling. Actually, the last portion of this equation is a form of correcting variations in the cooling rate of the test sample. This equation was developed using thermal analysis data collected during the air cooling of hot rolled samples[5].

Up to this moment there is very little information about the quantitative influence of alloy elements over the Ar_1 temperature, so no model was proposed for its calculation[2].

The aim of this work was to determine the T_{nr}, Ar_3 and Ar_1 temperatures for the most processed microalloyed steels at the COSIPA plate mill, as well to develop mathematical models for its calculation from the plate chemical composition.

2. Experimental Procedure

Hot torsion tests, using the methodology proposed by Boratto et al.[2], were carried out at the Materials Engineering Department of the Federal University of São Carlos, in São Carlos, Brazil. Ten microalloyed steels were studied, whose chemical compositions are shown in Table I.

	C	Mn	Si	Al	Cr	Cu	Nb	V	Ti	N
N1	0,18	1,34	0,30	0,025	-	-	0,033	-	-	0,0074
N2	0,14	1,02	0,27	0,035	-	-	0,020	-	-	N/A.
N3	0,15	0,77	-	0,039	-	-	0,014	-	-	N/A.
NT1	0,14	1,11	0,30	0,044	-	-	0,020	-	0,015	0,0054
NT2	0,14	1,34	0,23	0,035	-	-	0,033	-	0,014	0,0048
NT3	0,10	1,12	0,30	0,040	-	-	0,013	0,020	-	N/A.
NT4	0,10	1,16	0,33	0,027	-	-	0,035	0,023	-	N/A.
NTV	0,12	1,50	0,31	0,038	-	-	0,047	0,051	0,020	0,0064
NCC1	0,16	1,03	0,41	0,029	0,54	0,23	0,025	-	-	0,0107
NCC2	0,13	0,99	0,38	0,042	0,50	0,22	0,014	-	-	0,0095

Table I: Chemical composition of the steels studied in this work, weight percent.

The hot torsion test specimens were firstly heated up to 1150°C under a heating rate of approximately 1.7°C/s. They were kept at this temperature for ten minutes. After this soaking stage, the specimens were cooled under a rate of 0.5°C/s down to 1050°C. From this point on, the cooling rate was increased to 1°C/s. Simultaneously, the hot torsion test effectively began: a hot deformation pass was applied every 20 seconds, with a strain degree of 0.2 and strain rate of 1.0 s^{-1}. Therefore, the passes had an interval of 20°C between each other. It was aimed to apply a total of 20 deformation passes, so the last pass was applied under a temperature of approximately 670°C. This procedure was repeated five times for each steel studied. The

results of these tests allowed the drawing of graphs between mean hot strength versus the inverse of the corresponding hot deformation temperature. The analysis of these graphics, according to the methodology defined by Boratto et al.[2], allowed the determination of T_{nr}, Ar_3 and Ar_1 temperature values.

The statistical analysis for the determination of the correlation between these critical temperatures and the corresponding chemical compositions of the studied steels was carried out using the software *Systat*.

A comparison of the values of T_{nr} calculated by equation **(1)** and **(2)** to **(4)** was also done, as well the calculation of Ar_3 values by equation **(6)**.

Finally, the neural network technique was used for the development of models for the calculation of T_{nr} and Ar_3 from the chemical composition of steels. Given the small amount of data available for these temperatures – only ten cases – this approach can not be used for the direct determination of these critical temperatures, as it requires a much greater amount of data for training and testing of the models. Instead of that, neural network models were developed for the determination of the mean hot strength versus the inverse of the hot deformation temperature graphs, starting from the chemical composition of the steel and assuming the same hot forming conditions described above. From that graph, T_{nr} and Ar_3 can be determined using the approach of Boratto et al.[2].

A previous performance analysis showed that best results were got using two individual neural networks. The first network generates a mean hot strength versus inverse of hot deformation temperature graph limited to the 1050 to 780°C temperature range; the second was developed for use in the 900 to 720°C range. The graphs they generated are respectively used for the determination of T_{nr} and Ar_3.

The neural networks used in this work were of the Rummelhart type, with three neuron layers. The first layer was used for the input of the necessary data for the calculations: the amounts of C, Mn, Si, Nb, Ti, V, Cr, Cu, Al and N, as well the deformation temperature. The second layer, also known as the hidden layer, is used to improve the learning capacity of the neural network. It had 23 neurons, according to the Hecht-Kolmogorov theorem[8], which proposes that the number of neurons in the hidden layer must be to the double of the neurons in the input layer (in this case, 11) plus one. The output layer had just one neuron, which is equal to the mean hot strength corresponding to the input data. The training and testing of these neural networks was done using the *NeuralWorks* software.

The evaluation of the statistical and neural networks models developed in this work was done comparing the corresponding values of the Pearson correlation coefficient **r** and the standard error of estimate.

3. RESULTS AND DISCUSSION

The results of T_{nr}, Ar_3 and Ar_1 got for the steels studied in this work are shown in table II. The determination of Ar_1 was not possible for all samples, due to the premature breaking of a significant fraction of the hot torsion specimens before reaching the range of temperatures corresponding to that parameter. The resulting lack of data prevented the determination of the correlation between Ar_1 and the chemical composition of the steels.

	T_{nr}	Ar_3	Ar_1
N1	868	730	-
N2	894	775	-
N3	879	712	-
NT1	861	772	-
NT2	899	753	-
NT3	840	760	-
NT4	918	748	-
NTV	916	754	697
NCC1	883	748	708
NCC2	894	754	707

Table II: Controlled rolling critical temperatures determined for the studied steels.

The results of the Pearson correlation coefficient showed that only Nb had significant effect on T_{nr}, with **r** equal to 0,634. The results of the principal component analysis showed that Mn, Nb and V are directly correlated to T_{nr}, as showed in Figure 2.

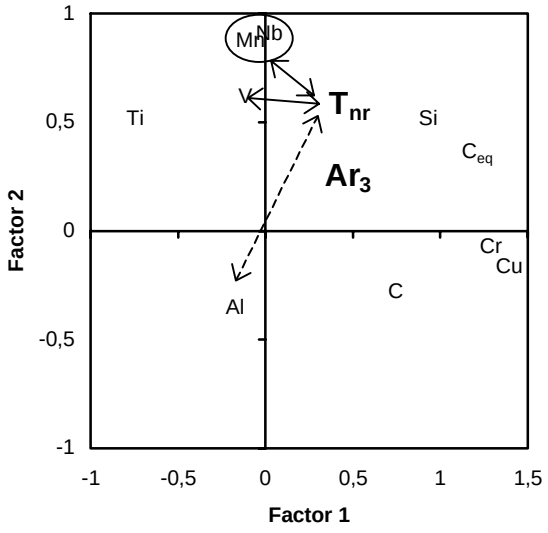

Figure 2: Principal component analysis graph between T_{nr} and the chemical composition of the studied steels.

The effect of Nb over T_{nr} was thoroughly checked in the literature[2]; for its turn, the influence of Mn and V detected here apparently stems from a statistical correlation between the amounts of those elements and Nb. In fact, the Pearson correlation coefficient **r** between the amounts of Mn and Nb is equal to 0.845;

this same parameter equals 0.672 between the amounts of Mn and V. The principal component analysis also showed a light negative influence of Al on T_{nr}.

Apparently only Si had a significant influence over Ar_3; the value of **r** corresponding to that correlation was about 0.600. Even the principal component analysis did not present any significant correlation. Possible reasons for this behavior can be associated to the few number of analyzed steels, as well the corresponding narrow range of alloy elements amounts.

It is interesting to notice the peculiar results that were obtained for the N3 steel, which had the minimum amount of microalloying elements. Surprisingly, its T_{nr} is not between the smallest ones. A possible explanation for that fact is the absence of Si in this steel. This element, according to the equation of Boratto[2], tends to decrease T_{nr}. Its absence, therefore, can exert an inverse effect. The same fact can have some relationship with the low value of Ar_3 determined for that alloy, as the presence of Si tends to increase that parameter[9].

Data in Table III allows a comparison between T_{nr} values measured in this work and calculated by the models of Boratto, Dutta and by the neural network developed here. Only steels with known N amount were considered for this analysis. This data reveals that the neural network had the best forecasting performance, while Dutta and Boratto models showed a slight greater error.

Steel	T_{nr} Boratto [°C]	ΔT_{nr} Boratto [°C]	T_{nr} or $T_{95\%}$ Dutta [°C]	ΔT_{nr} Dutta [°C]	T_{nr} NN [°C]	ΔT_{nr} NN [°C]
Nb1	886	18	881	13	872	4
NbTi1	887	26	881	20	877	16
NbTi2	898	-1	902	3	897	-2
NbTiV	895	-21	905	-11	911	-5
NbCrCu1	878	-5	880	-3	892	9
NbCrCu2	878	-16	872	-22	873	-21
S.E.E.	20		17		14	

Table III: Values of T_{nr}'s calculated using the several models described in this paper: Boratto, Dutta and the neural network.

Firstly the performance of the Boratto equation will be analyzed. This formula was originally developed using data from almost fully solubilized microalloyed steels, which were austenitized at 1260°C before the hot torsion tests. Therefore, T_{nr} values calculated by this model in table III considered the corresponding solubilized amount of microalloying elements at the austenitization temperature used in this work, that is, 1150°C, calculated by a thermodynamical solubilization model for multimicroalloyed steels[10]. Such correction significantly increased the precision of the T_{nr} values calculated by the Boratto's model.

One can observe that Boratto's model presented tendency to overestimate the values of T_{nr}, except for the steels NbTiV and NbCrCu. In the last alloy, this fact can be attributed to the presence of Cu, once there is some evidence that this element also restricts austenite recrystallization, contributing to the elevation of T_{nr}[11].

Other deviations observed between Boratto's equation and the experimental data got in this work can be attributed to experimental dispersion and the different methodologies adopted in the tests of both works.

The model of Dutta also tended to overestimate the values of T_{nr} (that is to say, $T_{95\%}$), but this was not true for the NbTiV and NbCrCu steels. That seems to be an additional indication of the effect of Cu over T_{nr} mentioned before.

The neural network model "learns" the relationships between data by itself, dispensing the previous definition of a relationship between the several variables. The values of T_{nr}, calculated from the graphs average hot strength versus inverse of temperature, determined by the neural network, were slightly higher than the measured values. It is curious to verify that, in spite of that model based its calculations directly from the experimental results, it also significantly underestimates the T_{nr} value in one of the NbCrCu steels. This case also corresponded to the maximum deviation between measured and neural network calculated T_{nr} values: 21°C.

On the other hand, it must be noted that the neural network calculated T_{nr} values were determined by an indirect way. That is, this model did not supply directly the calculated T_{nr} values, but instead the graph between mean hot strength versus the inverse of temperature, which is used to determine T_{nr} using Boratto's methodology. Once that determination frequently involves subjective judgement for the analysis of the curves, particularly when the intersection between the two straight lines is ill conditioned, its precision can be harmed by random errors. Unfortunately, as T_{nr} data is scarce in this work, the development of a neural network model for its direct determination from steel chemical composition is not possible at this moment. However, this still is a possibility in the future, if more data becomes available.

Table IV shows the result of the comparison between experimental and calculated values of Ar_3. Two models were used for the calculation of this parameter: Ouchi and the neural network.

Steel	A_{r3} Ouchi [°C]	ΔA_{r3} Ouchi [°C]	A_{r3} NN [°C]	ΔA_{r3} NN [°C]
Nb1	740	10	728	-2
NbTi1	762	-10	761	-10
NbTi2	748	-5	756	3
NbTiV	744	-10	758	4
NbCrCu1	753	5	754	6
NbCrCu2	764	10	753	-1
E.P.E.	10		7	

Table IV: Values of Ar_3 calculated using the Ouchi and neural network models.

In the same way as observed for T_{nr}, only steels with known amount of N were considered in this analysis. The neural network model showed slight better

performance than Ouchi's formula. However, in both cases, Ar_3 determination was more precise than T_{nr}. Besides that, both Ar_3 models showed random errors, with no tendency to over or underestimate the experimental results.

Data scarcity problems that affected the T_{nr} neural network model also occurred during the development of the Ar_3 neural network model. This problem will be solved as more data becomes available. In fact, some papers about the development of neural networks models for the calculation of Ar_3 were already published, although they considered data from conventional CCT diagrams, where steel is not previously hot formed before cooling[12,13].

4. CONCLUSIONS

This work about mathematical models for the calculation of the critical temperatures of controlled rolling (T_{nr}, Ar_3 and Ar_1) from steel chemical composition arrived to the following conclusions:

- The effects of the chemical composition over Ar_1 could not be investigated due to the premature breaking of the hot torsion test specimens submitted to multiple passes;
- The element with largest influence over T_{nr} was Nb; Mn and V presented considerable influence, but there are doubts if their effects are legitimate or if they derive from a correlation with the Nb amount of the steels studied in this work. Apparently Si indeed tends to decrease T_{nr}, as observed in one of the alloys. It was also verified a slight negative influence of Al;
- A statistical analysis about alloy elements influence over Ar_3 showed that only Si exerted a significant influence. This fact was confirmed by the low Ar_3 value corresponding to a particular alloy which did not included this element;
- The comparison between several mathematical models used for the calculation of T_{nr} showed that their performance is better along the following sequence: Boratto $\rightarrow$ Dutta $\rightarrow$ Neural Networks;
- Also the neural network model for calculation of Ar_3 presented better performance than an empirical model, in this case, the Ouchi formula;
- A serious limitation of the neural network models developed in this work is the narrow range of alloy element amounts present in the data sets used for its training. This fact severely limits the chemical composition input values that can be used for the calculation. A more general and precise neural network model for T_{nr} and Ar_3 calculation would demand data of dozens of alloys.

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Nomenclature

T:	Temperature (K)
R:	Universal Gas Constant (J/K mol)
Z:	Zener-Hollomon Parameter
ε:	True Strain
k_s:	Niobium Supersaturation Ratio
d_o:	Initial Austenitic Grain Size (μm)
t:	Time (s)
h:	Thickness (mm)

References

1) DUTTA, B. & SELLARS, C.M. *Materials Science and Technology*, March 1987, 197-206.

2) BORATTO, F. et al. In: THERMEC ´88. Proceedings. Iron and Steel Institute of Japan, Tokyo, 1988, p. 383-390.

3) MACCAGNO, T.M. et al. *ISIJ International*, November 1994, 917-922.

4) LOTTER, V. et al. *Thyssen Technische Berichte*, 1984, 13-26.

5) OUCHI, C. et al. *Transactions of the ISIJ*, 22(3):214-222, March 1982.

6) ROBILLER, G. et al. *Stahl und Eisen*, 9 Februar 1987, 111-114.

7) BAI, D.Q. et al. *Metallurgical Transactions A*, October 1993, 2151-2159.

8) HECHT-NIELSEN, R. Neurocomputing. Addison-Wesley Publishing Company, Reading, 1991. 433 p.

9) CHOQUET, P. et al. In: INTERNATIONAL CONFERENCE ON STRENGTH OF METALS AND ALLOYS. Proceedings. Canadian Institute of Metallurgy, 1985.

10) GORNI, A.A. In: Spreadsheets in Science and Engineering. Springer-Verlag, Heidelberg, 1998. 289 p.

11) ABE, T. et al. *Transactions of the ISIJ*, 1987, 478-84.

12) DONADILLE, C. e al. *La Revue de Metallurgie – CIT*, Oct. 1992, 892-894

13) VERMEULEN, W. et al. *Steel Research*, Feb. 1997, 72-79.