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Modeling the Hardening of Carbon Steels After Quenching and Tempering

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Abstract. **In the paper, after an overview and defined tasks, a methodology is applied and a model is derived for establishing the dependence of hardness on carbon content, hardness after hardening and tempering temperature after hardening for the entire range of carbon steels from structural to tool steels. The research was based on eight steels and four tempering temperatures formed in a total of 32 combinations. First, one-dimensional dependences of hardness change on carbon content were derived for each annealing temperature, then accuracy was improved with a three-control parameter model. The derived model was examined and its theoretical maximum was corrected. The difference between the theoretical and the real logical maxima amounts to 17.44%. For all specified extremes, the heat treatment modes are defined.**

Keywords: hardness, quenching, tempering, matematic modes, carbon steel, multifactorial analysis.

I. INTRODUCTION

Clarification and evaluation of the possibilities of different types of strengthening have always interested researchers not only because of the significant application of this effect, but also because of the complexity of the processes taking place in it. Whether superficial or volumetric, hardening is primarily evaluated by hardness. Modeling the hardness of steels depending on the chemical composition, from the point of view of the physics of metals, is generally a difficult to formulate and unsolved task. The problem is that mechanical hardness at the atomic level is based on electrostatics and elastic shear, which can be generalized only for single-phase annealed alloys, and consequently only semi-empirical dependences can be obtained. Such an approach is used in [1], [2], [3], [4], [5], [6], [7] and [8] where, after adaptation, the interaction between dislocations and alloying elements is included. This interaction has been applied to eight two-component and three three-component alloys. In the cited research, a discrepancy between two of the main equations was found, and it was necessary to correct them with certain coefficients.

Simulation of the hardness is done because of the cooling rate during hardening of the steels. In such studies, the change in the temperature field is simulated by analyzing the phase transformation kinetics and modifying the hardness calculation model: [9], [10], [11]. In the cited research, when comparing the simulation results and the experimentally measured values, a good match between them was found. Very often, simulations are related to approximation from stiffness data, which can also be done by modeling with artificial neural networks with multilayer topology. An example of this is [12] where the relationship between phase composition and hardness of high entropy alloys (HEA) is investigated. Chemical composition was used as a set of input characteristics. In prediction, the neural network was trained with 775 experimental samples with a prediction accuracy of 93.4%. Despite the unprecedentedly large data set, for stiffness the model showed an average regression value of 0.88, and most of the predicted values that these authors indicate [13], are within the margin of error of 20%. Again by artificial neural network in [14] a prediction of the effect of chemical composition and tensile properties on both the impact strength and hardness of microalloyed steels intended for pipe manufacture was made. Such research requires, as noted, a larger number of observations, in the case of 104. Nevertheless, the role of the individual alloying elements is addressed implicitly, only through a single variable – "carbon equivalent based on the Ito-Bessyo equation (CEPcm)", as well as the "yield strength (YS)", the tensile properties. "ultimate tensile strength (UTS)" and "elongation (El)" are considered together as input parameters of the networks, while Vickers microhardness

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with applied load and Charpy impact energy are taken as outputs of the constructed models. Such generalizations will require the need for additional calculations with certain approximations. Without implicit forms for the properties and additional calculations, using a Russian database, six numerical author approaches are developed in [15], where, in addition to artificial neural networks and a carbon equivalent approach for small databases, a polynomial regression approximation is also applied. The research is done for seven control parameters of low-alloy steels with grain sorbite structure. This approach is also known as "Design of alloys". The amount and combinations of the alloy composition in this case offer the opportunity to specify properties-oriented compositions and modes of strengthening technologies. The research [16], [17] are also devoted to similar questions.

II. METHODOLOGY OF THE EXPERIMENT

Based on the overview, regardless of the variety of applied methods, the following more important conclusions can be drawn:

2.1. There is constant development in the field of mechanical properties of carbon steel, but almost all approaches used have been through experimental processes that are summarized with applied modeling. For it, it is always necessary to have pre-collected experimental data which, as a sample, are related to the approach to be applied.

2.2. The approach (from empirical, automated to the use of artificial intelligence) and the sample are related to the research object and this significantly affects the accuracy of the obtained decision.

2.3. A limited number of investigations have been devoted to the polynomial regression approximation, for which there is no research on modeling the hardness of the quenching mode after quenching (alloy quenched and tempered steel) considering the change of hardness after quenching and the chemical composition of the steel, expressed by the carbon content.

2.4. In widely available tools such as Excel and in the literature, solutions to assist the researcher in making decisions with more than 2 control parameters are absent. Based on the conclusions drawn, the purpose and tasks of the research were formulated.

In the available literature, the change of the hardening after quenching and tempering (quenched and tempered steel) depending on the carbon content has been numerically confirmed, Table 1. This trend for seven carbon compositions (8 steels) and 4 tempering temperatures is plotted in Fig. 1.

TABLE 1. NATURAL AND CODED INPUT AND OUTPUT PARAMETERS FROM THE TASK STATEMENT

№	X_1 [%] –carbon content in the steel	X_1 [/] –encoded value	X_2 [/]– HRC after quenching	X_2 [/]–encoded value	X_3 [ºC] – temperature at tempered	X_3 [/] –encoded value	HRC [/] –after quenched and tempered
1	0,31	-1,00	44	-1	180	-1	42
2	0,36	-0,89	48,5	-0,53846	180	-1	47
3	0,46	-0,66	52,5	-0,12821	180	-1	50,5
4	0,695	-0,13	62	0,846154	180	-1	61
5	0,795	0,10	63,5	1	180	-1	62
6	0,795	0,10	63,5	1	180	-1	62
7	0,995	0,55	63,5	1	180	-1	62
8	1,195	1,00	63,5	1	180	-1	61
9	0,31	-1,00	44	-1	300	-0,25	36
10	0,36	-0,89	48,5	-0,53846	300	-0,25	41
11	0,46	-0,66	52,5	-0,12821	300	-0,25	45
12	0,695	-0,13	62	0,846154	300	-0,25	54
13	0,795	0,10	63,5	1	300	-0,25	54
14	0,795	0,10	63,5	1	300	-0,25	54
15	0,995	0,55	63,5	1	300	-0,25	54,5
16	1,195	1,00	63,5	1	300	-0,25	53
17	0,31	-1,00	44	-1	400	0,375	30
18	0,36	-0,89	48,5	-0,53846	400	0,375	34
19	0,46	-0,66	52,5	-0,12821	400	0,375	40
20	0,695	-0,13	62	0,846154	400	0,375	48
21	0,795	0,10	63,5	1	400	0,375	48
22	0,795	0,10	63,5	1	400	0,375	48
23	0,995	0,55	63,5	1	400	0,375	48,5
24	1,195	1,00	63,5	1	400	0,375	48
25	0,31	-1,00	44	-1	500	1	22
26	0,36	-0,89	48,5	-0,53846	500	1	26
27	0,46	-0,66	52,5	-0,12821	500	1	31
28	0,695	-0,13	62	0,846154	500	1	42
29	0,795	0,10	63,5	1	500	1	41,5
30	0,795	0,10	63,5	1	500	1	41,5
31	0,995	0,55	63,5	1	500	1	42,5
32	1,195	1,00	63,5	1	500	1	43

III. Analysis of Results

From the visualization of the data, all postulates known from the theory are confirmed:

- The carbon content has a significant influence on the hardening and the tendency to increase the hardening is maintained as a similarity among the investigated tempering temperatures.
- As the tempering temperature increases, the hardening decreases, and at 180 °C tempering it is negligible, applied to remove internal stresses for tools, while at 500 °C tempering it is applied to improve the grain structure, increasing the strength of blow.
- Based on the experimental data presented in Fig. 1 using the widely spread Excel, relationships predicting the unexamined carbon content at a specific retort temperature are derived. The results of this modeling are presented in Table 2

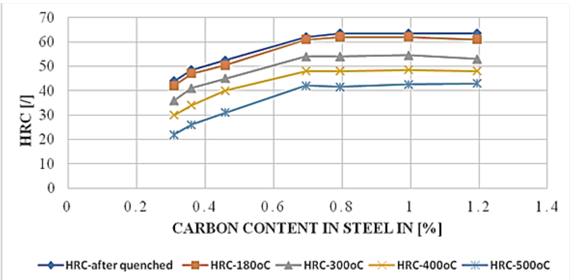

Fig. 1. Effect of carbon content and annealing temperature on hardening

Table 2. Hardness patterns as a function of carbon content and tempering temperature

№	Speed, mm/ min	Hardness model as a function of carbon content	Correlation coefficient
1	Heating in the range 860 – 760 °C and quenching while cooling in water	y = – 44,813×X^2 + 87,888×X + 21,83	R^2 = 0,9904
2	Tempering and quenching at 180 °C	y = – 49,202×X^2 + 93,996×X + 18,388	R^2 = 0,9886
31	Tempering and quenching at 300 °C	y = – 46,132×X^2 + 86,689×X + 14,741	R^2 = 0,9848
4	Tempering and quenching at 400 °C	y = – 44,671×X^2 + 85,446×X + 8,8962	R^2 = 0,9815
5	Tempering and quenching at 500 °C	y = – 45,045×X^2 + 89,816×X – 0,8252	R^2 = 0,9828

Models from the polynomial regression approximation of hardness from the carbon state are plotted in natural units, along the abscissa axis in Fig. 1; the peculiarity of these models is the relatively low coefficient of multiple correlation for the models describing the return. Sufficient experimental data are available through which the accuracy of the modeling can be improved. One of these possibilities is by using the coded values from Table 1.

The disadvantage of this kind of representation is the low dimensionality of the modeling; for this reason, it does not comprehensively cover all examined indicators that are controlled. To overcome this shortcoming, the aim of the research is formulated: by means of modeling, the influence of the change in composition and the tempering temperature on the hardening of carbon steels after hardening heat treatment can be identified. Quenching and tempering (Q&T alloy quenched and tempered steel) is a combined heat treatment process to achieve maximal hardness with a certain strength and ductility. The goal of the research is to develop a mathematical model for the quenching and tempering process for the entire range of carbon steels – both structural and tool..

The results of the experiment are used to obtain the mathematical model of the examined process. A mathematical model is a system of mathematical relationships that describe the process or phenomenon under research. When planning an experiment, a mathematical model is often understood as an equation that relates an optimization parameter to factors. This equation is also called the response function. For the data from Table 1, in coded form, the model for the hardness depending on the carbon content of the steel X_1, the hardness after quenching X_2 and the tempering temperature X_3 is derived.

$$\begin{aligned} HRC = {} & 47.9658 + 6.80107\times X_1 + 2.60967\times X_2 \\ & - 9.54842\times X_3 - 0.149884\times X_1^2 - 7.06309\times X_1\times X_2 \\ & + 0.850104\times X_1\times X_3 + 1.79414\times X_2^2 - \\ & 0.448902\times X_2\times X_3 - 0.598823\times X_3^2 \end{aligned} \tag{1}$$

Polynomial regression analysis was used as the algorithm to express the model, and the programming language – Authoring Decision Support System was used to interpret the model results. The model data, which are the predicted stiffness values, were validated using an F-test combined with mean, correlation coefficient, and standard error analyses. The finding of improvement in accuracy at coded values for which the model was derived actually occurred with all control parameters considered together. The multiple correlation coefficient for the resulting model increased to $R^2 = 0.9977$. The adequacy of the model is also proven by Fisher's test, where the calculated value in this test is extremely much larger: $538.3673 >> 2.3419_{(a=0.05,\,9.22)}$ than the one determined in the table.

Analysis of the mutual influence of a set of three, four or more controlled parameters is difficult and requires an "advisor" developed as a system that takes into account:

- The exact complex interaction between parameters such as value and normalized percentage of the maximum. The interaction is visualized and can be justified iteratively by refining color intervals.
- A friendly oriented system, initially working with colors and upon reaching the desired solution for a maximum or minimum, the values of the control parameters and the investigated quantities are specified [18].
- The system is successfully applied to determine a complex of properties of a contradictory nature.

Using the cited decision support system, the following extremes of model (1) were obtained. Table 3 shows the minimal and maximal stiffness, as well as the values of the control parameters at which these values occur.

TABLE 3. MAXIMA AND MINIMA OF MODEL-DETERMINED STIFFNESS

№	HRC	X1 C [%]	X2 HRC after quenching	X3 T [°C]
1	Minimum – 22.6 [0 %]	0.31	44	500
2	Theoretical maximum – 68,51 – [100 %]	1.195	44	180
3	Real logical maximum – 61.1 –[82,56 %]	1.195	63.5	180

Based on the analysis, it was found that the theoretical maximum is unrealistic and it is 17.44 % greater than the actual logical one.

IV. CONCLUSION

Through the means of modeling in a new way, it has been proven that tool steels are always tempered at low temperatures in the range of 150 – 200 °C. This is proven by the derived model in which, after analysis, it was necessary to adjust its theoretical maximum. The difference between the theoretical and the real logical maxima amounts to 17.44 %. The analysis was performed by means of a system applied in varying the parameters of a technological process of retort for seven steels in order to identify the parameters of the process thickness.

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