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INFLUENCE OF PROCESS PARAMETERS ON THE PROPERTIES OF AUSTEMPERED DUCTILE IRON (ADI) EXAMINED WITH THE USE OF DATA MINING METHODS

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The article presents opportunities offered by the data mining analysis as applied to studies of the effect of process parameters on the mechanical properties of ADI. The applied methods of regression trees and cluster analysis allow for the detection of relationships between parameters and also allow determination of strength and form of the impact of different factors. The results of this study allow the creation of knowledge bases for systems supporting the decision-making process in technology.

Key words: ADI, mechanical properties, temperature, data mining, cluster analysis

INTRODUCTION

Austempered Ductile Iron, known as ADI, is a very interesting cast material due to (1) high mechanical properties which, compared to other types of cast iron, make ADI an excellent alternative for certain steel grades and even aluminium alloys, and (2) relatively low cost of production compared to steel and aluminium. ADI has a high fatigue strength, is resistant to wear and abrasion, and offers good toughness [1]. ADI has well proven functional properties, which make it a very attractive material for the manufacture of components used in various sectors of industry such as automotive, rail transportation and agriculture [2]. The use of ADI allows reducing the cost of production process, among others, due to its high fluidity enabling the near-net-shape manufacture of intricate parts and good machinability before the heat treatment increasing the life of tools [3, 4].

The price to pay for such attractive features is the demanding high precision process of casting production preparation. ADI is made by spheroidization of the base cast iron with a specific chemical composition, followed by heat treatment involving the process of austenitizing and isothermal transformation [5, 6]. Parameters defining this process include chemical composition, temperature and time of austenitizing (TA, tA), and temperature and time of isothermal transformation (Ti, ti). Changes in these parameters affect the structure of material, and consequently also its properties [7]. Alloying additions such as Cu and Ni can reduce the fatigue strength [8]. Important parameters are: tensile strength, yield strength, fracture toughness and elongation [9]. Analyzing the effect of the temperature of ausferritizing treatment on the resistance to cracking it can be noted that with increasing temperature the fracture toughness initially increases up to approx. 316 °C and then declines [10]. At lower temperatures of ausferritizing the yield strength, tensile strength and hardness are lower [11].

More comprehensive discussion of the ADI production process the Reader can find in earlier publications of the Authors [12, 13], however in this paper we include new additional important information.

Based on previous studies, data was collected on the ADI manufacturing process carried out under various conditions. The data covered 196 records discussing various heat treatment scenarios and chemical compositions.

Table 1 **Ranges of values of individual process variables for collected process variants**

	average	minimum	maximum	s. deviation
C	3,49	3,21	3,85	0,17
Si	2,60	2,13	3,25	0,24
Mn	0,27	0,12	0,61	0,09
Mg	0,05	0,02	0,15	0,03
Cu	0,29	-	1,44	0,38
Ni	1,09	-	2,26	0,67
Mo	0,15	-	0,47	0,15
S	0,01	-	0,02	0,00
P	0,04	-	0,08	0,02
Cr	0,02	-	0,05	0,02
TA/ °C	902,3	830,0	950,0	27,4
tA/ s	6 502,0	3 600,0	7 200,0	1 317,9
Ti/ °C	330,3	230,0	400,0	41,8
ti/ s	8 399,2	900,0	28 800,0	5 860,8
tensile strength/ MPa	1 187,7	719,0	1 602,0	194,8
elongation/ %	5,9	0,0	20,0	3,7
hardness/ HRC	36,1	21,5	51,0	6,7
yield strength/ MPa	914,0	455,0	1 418,0	206,9

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REGRESSION TREES

The CART (Classification And Regression Trees) algorithm of regression trees allows predicting the continuous dependent variable based on variations of the independent variables. The essence of the algorithm is the division of the range of dependent variable into classes characterized by a mean and a variance. These classes group cases with similar characteristics based on the similarity of attribute values, which are the explanatory variables. This algorithm is known from the literature. It was developed by Brainman [14] and gained fame owing to the use by Quinlan [15]. It is currently widely applied as part of the STATISTICA software package [16]. The advantages of this algorithm mainly include easy interpretation of results and efficacy higher than the efficacy of other techniques for induction of decision trees [17]. Trees induction algorithm iteratively divides the learning data set into partitions, performing this operation until each partition shows a strong similarity between the objects. The division is based on a least squares deviation criterion for regression trees.

This allows for the construction of decision rules based on explanatory (independent) variables. Decision trees are a graphical representation of the rules in user-friendly form [18]. CART algorithm enables not only the creation of rules, but also determines the validity of individual variables in a model. The variable is defined as important in the process of regression, or requesting information on classes, depending on its readiness to participate in the successive divisions of the dependent variable, which is measured during the construction of the tree.

In industrial applications and measurements, less expensive methods of classification and regression are applied, to mention as an example the k-nearest neighbours method, neural networks [19] or methods based on patterns and measures of the distance [20]. However, none of these methods allows for the induction of rules, and thus for the acquisition of new knowledge about the phenomena.

The resulting knowledge can be formalized by means of logic programming languages - binary or multiple-valued logics such as fuzzy logic or logic of plausible reasoning are used here. Thus stored knowledge allows for building of intelligent systems to support the decision-making process in the field of technology [21].

The use of regression trees in this study allowed the generation of 16 rules for the dependent variable: tensile strength, 18 rules for elongation, 11 rules for hardness and 9 rules for the dependent variable: yield strength.

Each dependent variable – which stands for a different mechanical property - depends to a different extent on the process parameters. Strength is the variable most dependent on the austenitizing temperature, but also on the content of C and Mg. Hardness is mainly related to the austenitizing temperature, but can be controlled equally well also by the content of Ni, S and Mo. Similarly, the yield strength depends on the temperature of austenitizing and on the content of Ni. A sample fragment of the decision tree for dependent variable: hardness is shown in Figure 1.

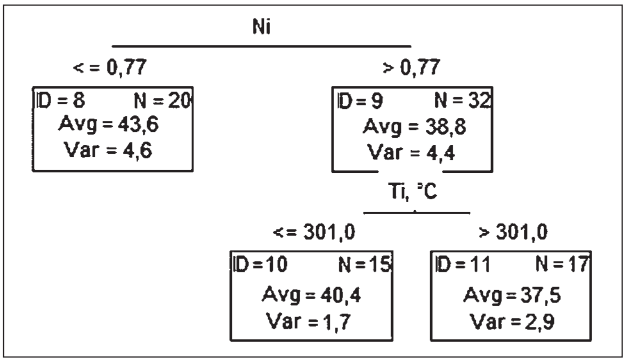

Figure 1 Fragment of regression tree for dependent variable: hardness

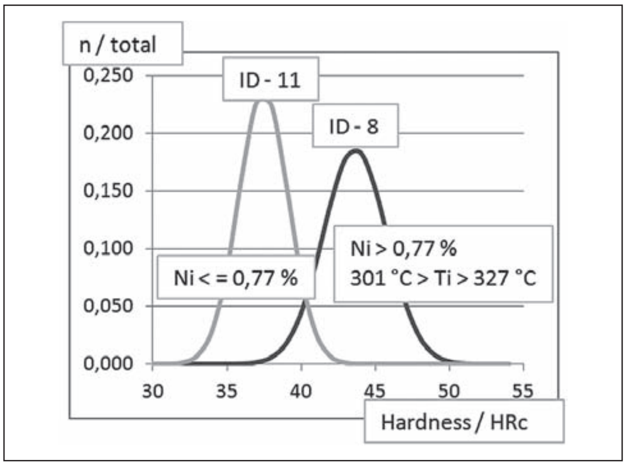

Figure 2 Effect of Ni content and isothermal transformation temperature on hardness

From the fragments of this tree it follows that under the maintained constant conditions (the cut off part of the root 284 °C < = Ti < = 327,5 °C; TA > 840 °C), in 52 cases, the Ni content>0.77% results in a decrease of the average hardness to 38.8 HRc. In this group, the decrease of hardness is also caused by the increasing temperature of isothermal transformation (Ti). These relationships are shown in Figure 2.

CLUSTER ANALYSIS

The weakness of regression trees is the possibility to establish only one dependent variable. Due to this, it is necessary to study separately the impact of individual factors on the variable properties. An integrated analysis of the impact of process parameters is possible by cluster analysis based on EM (Expectation Maximization) method [22]. This method allows grouping of objects into clusters based on the values of characteristic features describing these objects (variables) using two-criteria optimization: minimizing the distance within the clusters and maximizing the inter-cluster distances (Figure 3).

Cluster analysis leads to the conclusion that e.g. the effect of nickel reduces hardness but raises elongation; shorter time of austenitizing raises hardness; high con-

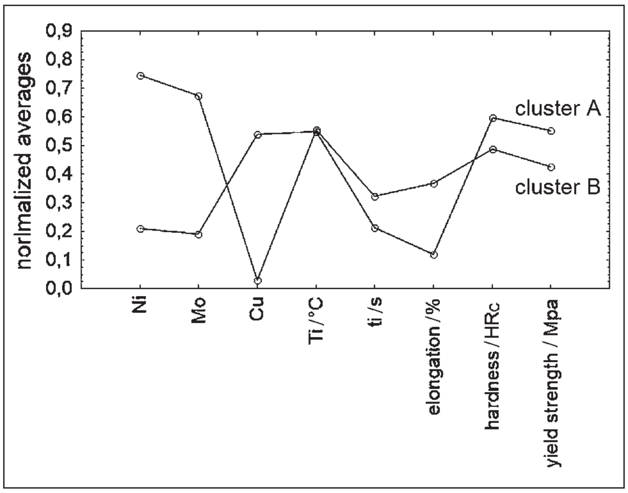

Figure 3 Chart of normalized averages in groups by properties (fragment)

tent of Cu results in low elongation, but high yield strength, etc.

CONCLUSIONS

The aim of this study was to determine the effect of parameters of ADI manufacturing process on the mechanical properties of products obtained. The study used data mining, in particular CART regression trees and cluster analysis by EM method. Owing to these methods it was possible to determine which of the factors present in the process had the strongest impact on the final properties of castings and to create rules for process control to obtain the expected end effects. Algorithmically acquired knowledge influences the improvement of ADI production process control.

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