Publishing House
AKAPIT

COMPUTER METHODS IN MATERIALS SCIENCE
Informatyka w Technologii Materiałów

Vol. 14, 2014, No. 3

MODELING OF AUSTEMPERED DUCTILE IRON USING DISCRETE SIGNALS

ANDRZEJ KOCHAŃSKI[1,*], PRZEMYSŁAW GRZEGORZEWSKI[2,3], ARTUR SOROCZYŃSKI[1], ANNA OLWERT[2]

[1] *Instytut of Manufacturing Technologies, Warsaw University of Technology,*
[2] *Systems Research Institute, Polish Academy of Sciences*
[3] *Faculty of Mathematics and Information Science, Warsaw University of Technology*
**Corresponding author: akochans@wip.pw.edu.pl*

Abstract

Austempered ductile iron is a perfect constructional material. Its unique properties combining high strength with good elongation follow from the material's structure, in which a special role is played by a metallic matrix. The growing requirements that cast producers have to meet result in the necessity of developing appropriate tools for the production process control. The present work discusses the state of the art with respect to the modeling of ausferritic ductile iron properties. Furthermore, it puts forward a new approach to the modeling of selected properties which is based on creating logical rules. The proposed approach has been verified with the use of the data set with the data coming from diverse sources and pertaining to more than 1400 melts. The results of the experiment have confirmed the usefulness of the proposed method. In the summary, the method's further potential development has been considered.

Key words: Austempered ductile iron, properties modeling, rules inducing

1. INTRODUCTION

Austempered ductile iron is a material characterized by very good constructional properties, which offer high strength combined with relatively high elongation or considerable elongation combined with good strength. These unique properties result from the material's structure, in which nodular graphite precipitations are evenly distributed in the matrix made up of ferrite blades and high-carbon austenite. The growing number of studies and the start-ups of new technological lines bear witness to the growing interest in this material as a potential alternative to the materials which have been in use up till now. As a result of its highly desirable properties, in combination with the low cost of its production, austempered ductile iron is now replacing other materials, such as aluminium (Fraś & Górny, 2010) or steel (Guzik et al., 2000). This is a very widespread phenomenon, encompassing such areas of use as the automotive industry (Bradenberg et al., 2002; Seaton & Xiao-Ming, 2002), the extractive industry (Raghavendra et al., 2010), or the area of food processing (Laino et al., 2011).

A database of austempered ductile iron properties has been developed in the Department of Metal Forming and Foundry (the Institute of Manufacturing Processes, Warsaw University of Technology). The data in the database come from the three basic sources:

– the research conducted by the Department's faculty members,
– the research conducted within other Polish research centers, whose results have been made available in a variety of publications,

 ISSN 1641-8581

- international publications presenting the results of specific experiments or the collective results of a number of experiments.

The developed database contains the data pertaining to more than 1400 melts and heat treatments, including nearly 250 melts with different chemical compositions. Each melt has been characterized in terms of 26 input parameters, such as:
- chemical composition – 14 elements,
- ductile iron properties (as cast) – 8,
- heat treatment parameters – 4 (two temperatures, two times),

as well as in terms of 8 output parameters, such as the mechanical and structural properties.

Figure 1 represents the distribution of silicone in the function of carbon in the melts from the developed database. Recently, the database has been enriched with the records pertaining to the melts which in the chart are marked with full dots. The results of the research pertaining to these melts are discussed in works (Kochański et al., 2014; Krzyńska & Kochański, 2014).

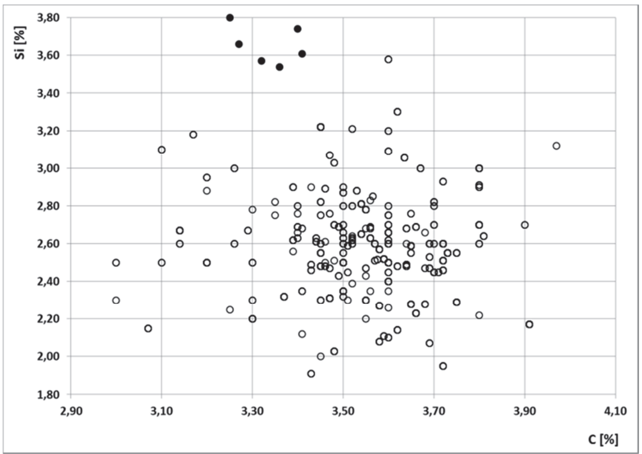
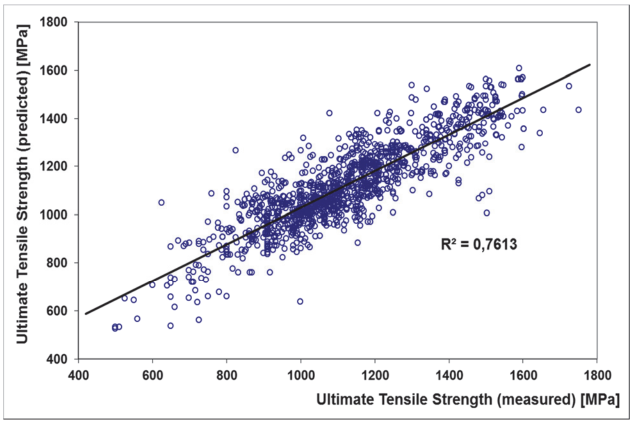


Fig. 1. The distribution of silicone in the function of carbon in the melts described in the database

2. MODELING PROPERTIES OF DUCTILE IRON

In modeling properties of ductile iron (Perzyk & Kochański, 2001) or austempered ductile iron (Kochański et al., 2012), it is the percentage of elements, such as – among others – C, Si, Mn, P, S, Cu, Mg, which is used as the input data. In the case of austempered ductile iron, what is taken into consideration is not only its chemical composition, but also the heat treatment parameters – the time and the temperature of austenitizing, as well as the austempering time and temperature.

To develop a model of the properties of ductile iron one may use diverse tools. In particular, artificial neural networks (ANN) turn out to be very useful there (Yescas et al., 2001; Biernacki et al., 2006; Kochański et al., 2010). An example of the results of the tensile strength modeling with the use of ANN is presented in figure 2. More specifically, figure 2a shows the distribution of predicted values considered as a function of the measured values, while figure 2b illustrates the proportion of the predicted cases with the prediction error falling within the following ranges: [0%,10%), [10%,20%), [20%,30%), [30%,40%]. The hatched area in figure 2b represents the proportion of cases with the prediction error lower than 5%.



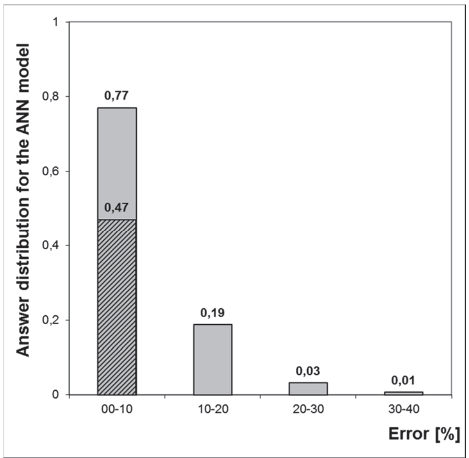


Fig. 2. Prediction error for ultimate tensile strength in ANN modeling (a) predicted vs measured error, (b) error distribution, (Kochański et al., 2012)

It is easily seen that all model parameters, as well as all the properties under modeling (e.g. tensile strength, elongation, hardness) are continuous variables. However, a closer analysis of the collected data set reveals that the attributes of interest take relatively few values. Examples of the distribution of the austenitizing time and the austempering time appearing in the available database are given in figure 3.

This noticeable discretization of input signals is relatively easy to explain, as it is – in a large measure – caused by a habit of dividing time into equal periods which are hour fractions: ¼, ½, ¾, 1, etc.

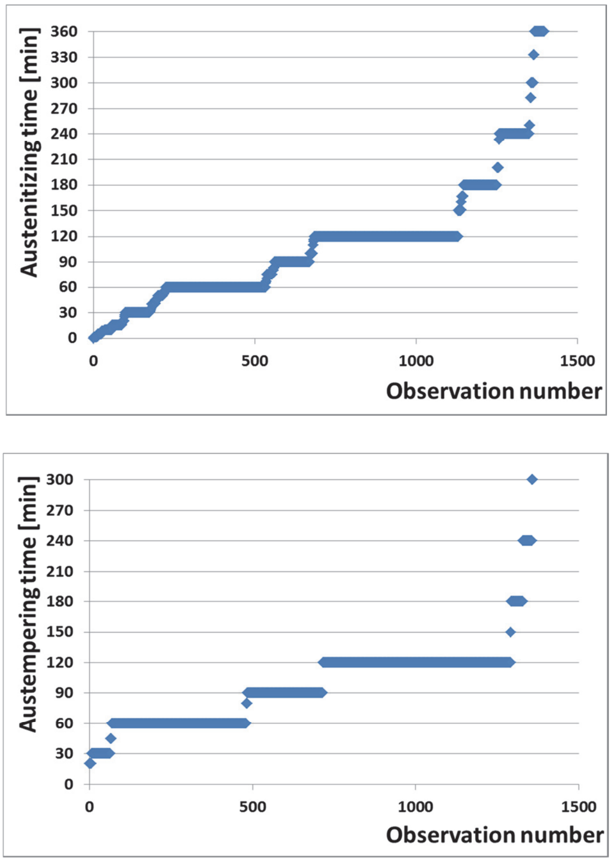


Fig. 3. *The distribution of austenitizing time (a) and austempering time (b) ordered increasingly*

From the perspective of the melt evaluation it is important that the product consumer's requirements are met. These requirements may be defined by a standard or any other agreements. The cast iron grades (the grades of ductile cast iron and austempered ductile iron) which are indicated by the standard are characterized in terms of the minimal values of the desired parameters such as, for instance, tensile strength or elongation (see figures 4a and b). To obtain a product (a casting) from a melt having the desired properties we need to keep the percentages of the particular elements within particular ranges (tolerances). The boundary values assumed in the following research which establish the low and high range or the low, medium, and high range for each of the parameters, are based on the industrial practice and the authors' own experience. Figure 5 represents an example of the distribution of the manganese content (%Mn) in the function of the silicon content (%Si) for melts conducted in one of Polish foundries. An analysis of such distributions made it possible to establish the range boundaries which were used in the following modeling.

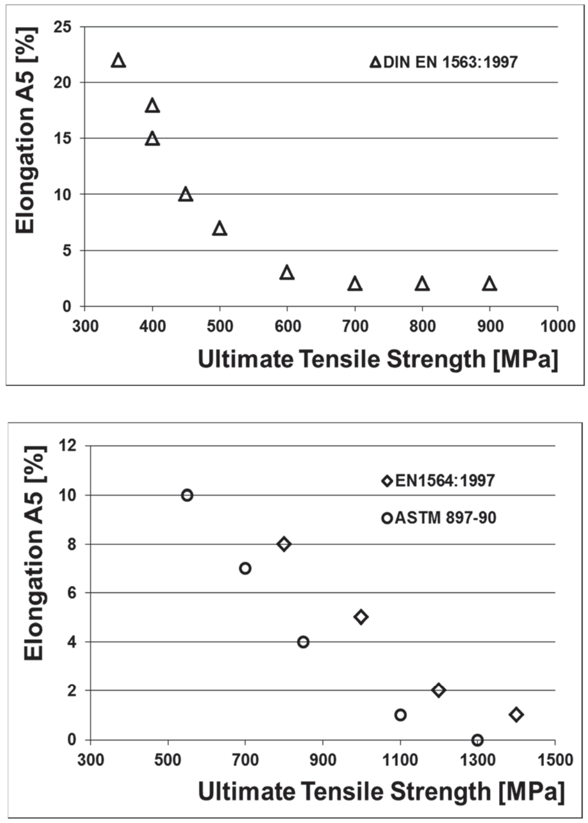


Fig. 4. *Elongation vs UTS according to American and British Standards for ductile cast iron (a) and austempered ductile iron (b)*

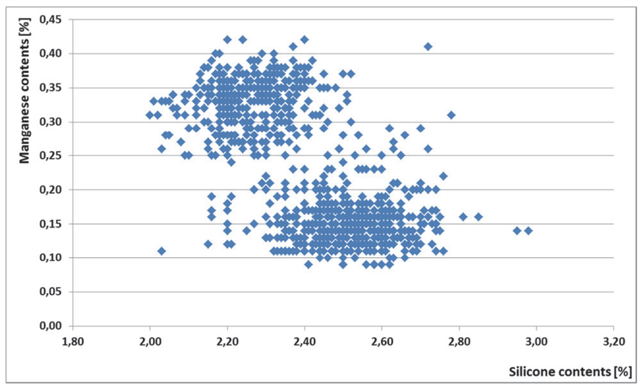


Fig. 5. *Distribution of manganese contents vs. silicone contents in the melts obtained in one of Polish foundryshops [own work]*

A similar approach is adopted in the research pertaining to the austempered ductile iron properties. For example, in (Guzik, 2006) the obtained matrix structure has been classified according to the high or low temperature (two levels) of isothermal quenching, with clearly represented temperature ranges of T_{pi} = 250÷300°C and T_{pi} = 350÷400°C.

The above-mentioned issues have encouraged us to describe the properties of austempered ductile iron by the use of tools employing discrete input signals. In particular, we have decided to develop a rule-based system consisting of the following rules:

IF (*attribute* 1 = … AND *attribute* 2 = …)
THEN output = … (1)

In the industrial practice, the available information on the basis of which the rules are generated may happen to be incoherent. This is the case when more than one decision is assigned to a single combination of attribute level. The reason behind the incoherence may be, for instance, the method employed for data acquisition and data recording. Despite the potential incoherence in the data, rule induction may be realized with the use of:

– rough sets,
– attribute level sets.

3. INDUCING RULES FOR DUCTILE IRON MODELING

To design a rule-based system for modeling properties of ductile iron, four basic element characterizing its chemical composition (i.e. carbon, silicon, manganese and magnesium) and one important heat treatment parameter (i.e. austempering temperature) were chosen as explanatory variables. Then appropriate labels were attributed to the content levels designated for each considered element: *low* or *high* – in the case of two content levels and *low*, *medium* or *high* – in the case of three content levels, further on denoted as *l*, *m* and *h*, respectively. Keeping in mind the order of elements (i.e. C, Si, Mn, Mg), four labels describing content levels of these

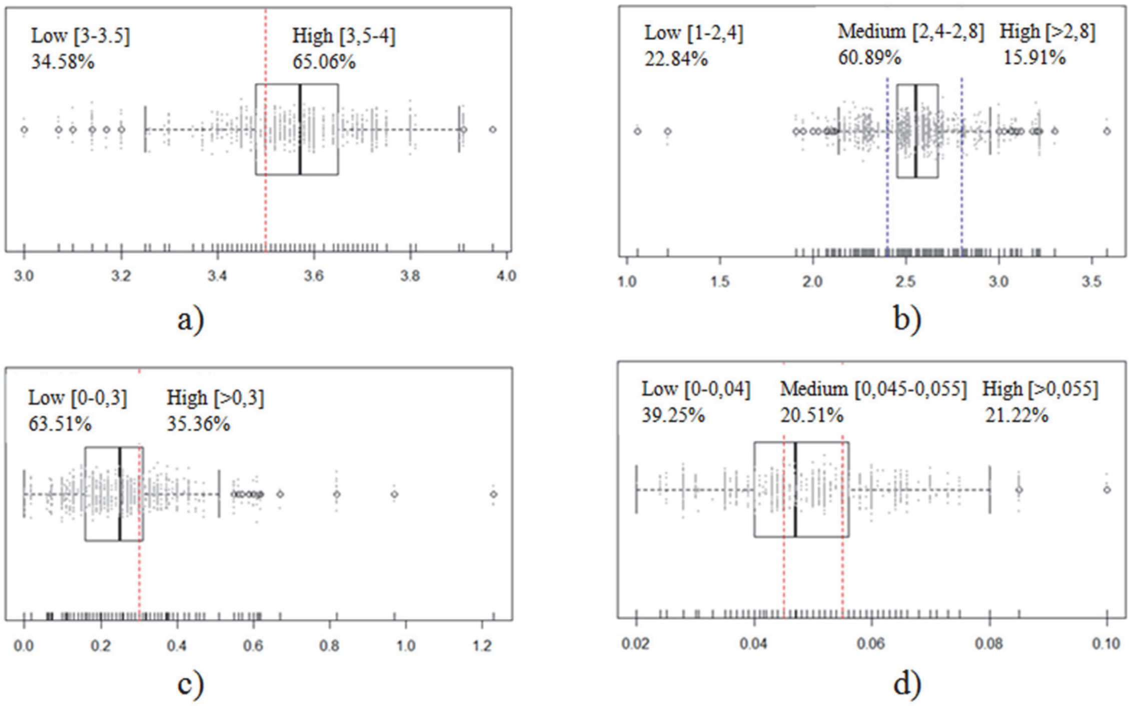


Fig. 6. *Borders for assumed feature levels and empirical distributions of carbon (a), silicon (b), manganese (c) and magnesium (d)*

An example of the rough sets approach for generating rules to predict austempered ductile iron tensile strength is discussed in (Kochański et al., 2013). However, in the present paper we will focused on the second approach mentioned above, i.e. on the attribute level sets.

To generate the attribute level sets one should:

– define discrete levels of the considered features (explanatory variables) and assign to them appropriate labels (e.g. *high*, *medium*, *low*),
– indicate all possible level configurations for the considered features,
– determine values of the explained variables corresponding to each feature configuration.

elements indicate all available feature configurations. For instance, *hmlh* denotes a specimen with high content of carbon, medium content of silicon, low content of manganese and high content of magnesium.

Box-and-whisker plots illustrating empirical distributions of the contents of these four elements, based on available database, are given in figure 6. The borders for assumed feature levels are also marked there. Moreover, the percentages corresponding to particular feature levels are also indicated. On the other hand the distribution of the feature configurations that occur most often in the available database is shown in figure 7.

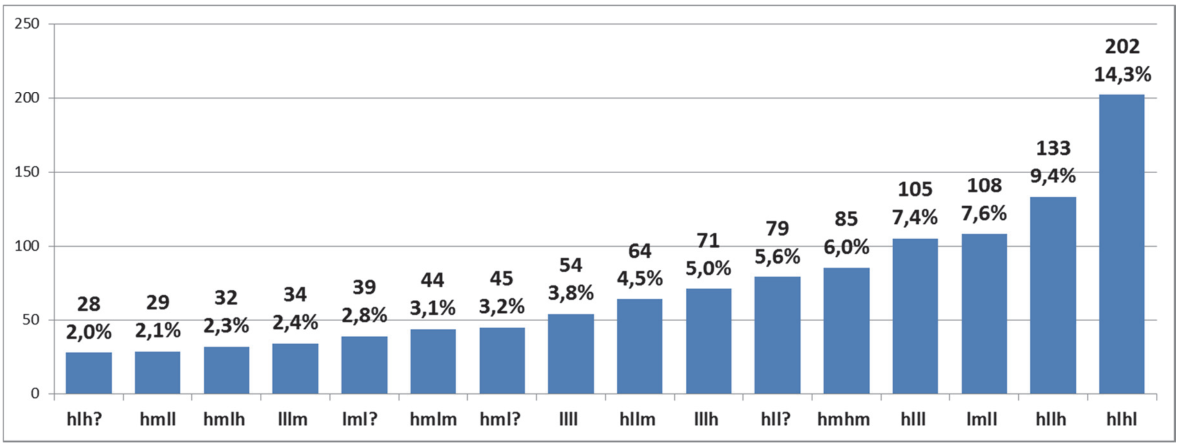


Fig. 7. *Feature configurations that occur most often in the available database (a corresponding frequency and percentage in given above each bar)*

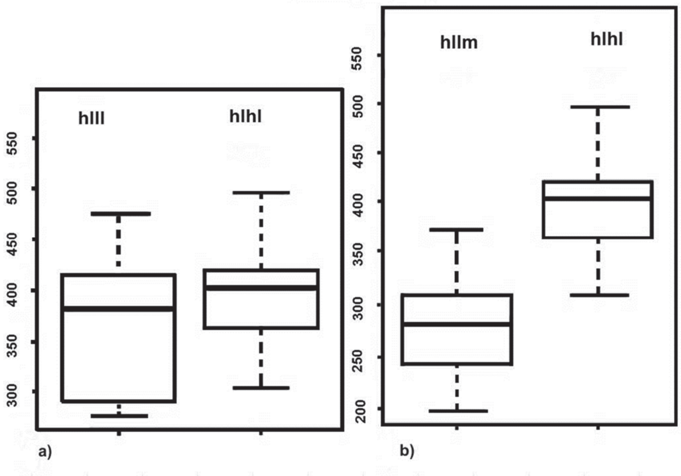


Fig. 8. *Brinell Hardness at low austemperig temperature and C, Si, Mn, Mg content corresponding to hlll and hlhl configurations (a) and hllm and hlhl configurations (b)*

It is worth noting that among most common (C, Si, Mn, Mg) configurations appear also configurations with unknown content of one element (in figure 7 this unknown content level is denoted by ?).

In this very point one may ask how to handle such configurations with missing data. Several solutions might be applied there. For example, one may attach a configuration with missing information to other configurations with identical content levels corresponding to the remaining elements. It could be done either at random or using some strategy.

Let us observe, for example, that the most frequent configuration of that type is *hll*?, i.e. a specimen with a high content of carbon, low content of silicon and manganese and unknown content of magnesium. Since our model admits three possible magnesium levels, hence *hll*? actually means either *hlll* (7,4%), or *hllm* (min. 4,5%) or *hllh* (min. 9,4%). Thus, in practice, one may expect that if C, Si and Mn contents are as mentioned above then the high or low content level of Mg is the more probable one.

4. ANALYSIS OF THE RESULTS

Box-and-whisker plots given in figure 8 show empirical distributions of the Brinell hardness for some feature configurations. More precisely, using multiple box-and-whisker plots we compare *hlll* and *hlhl* configurations and then another pair of configurations: *hllm* and *hlhl*.

Data in both cases were obtained for low austempering temperature.

Measurements of the Brinell hardness for two feature configurations characterized by different contents of manganese (low and high) and identical content of carbon (high), silicon (low) and magnesium (low) are compared in figure 8a. One can easily observe a definitely smaller interquartile range of the hardness for a sample with a high content of manganese. The lower (first) and upper (third) quartile for this feature configuration *hlhl* equal 360 and 420 HB, respectively. On the other hand, if the manganese content is low then for fixed contents of the remaining three elements it is possible to achieve a significantly bigger range of hardness. Actually, in that case (i.e. for *hlll* configuration) the lower and upper quartile for this feature configuration equal 290 and 420 HB, respectively. It is also worth noticing that the median of these two configurations under study remains nearly constant and takes vales equal to 380 and 400 HB, respectively.

In figure 8b we compare two feature configurations that differ in a content of two elements: manganese and magnesium. The first sample corresponds to a cast iron characterized by a low content of manganese and a medium content of magnesium, while the content of these two elements in the second sample is high and low, respectively. It should be stressed that the interquartile range in both cases is quite small and is about 60 units. However, medians in both samples differ a lot. Indeed, an increase of manganese level from the low to high with a parallel change of magnesium content from the medium to low results in a considerable growth in the average hardness from 280 HB to 400 HB.

5. CONCLUSIONS

The suggested method combining the generation of attribute level sets with a graph analysis seems to be a useful tool which simplifies initial interpretation of the models of the properties of the ductile iron. Box-plots, well-known in descriptive statistics, enable a relatively quick assessment of a role played by particular features or by sets of attributes. Moreover, a comparison of location parameters (like median) and measures of dispersion (e.g. interquartile range) may be helpful in indicating features having a significant impact on some important characteristics of ductile iron. The same tools may also point out features that do not affect some characteristics under study. A change in a level of one variable or a few variables results in a change of the dependent variable median (i.e., the property under analysis). The size of this dislocation (small or big) indicates, respectively, weak or strong impact of the parameter (or the parameter combination) for which the level was changed. Another advantage of the suggested approach is a possibility of considering continuous variables explained without a necessity of their preceding discretization. This results directly from the box-plot construction which illustrates a sample using its main summary statistics without any initial preprocessing (including discretization).

The methodology proposed in this paper requires, of course, some further studies. In particular, it would be desirable to enrich a set of statistical tools and procedures that enable testing significance of each feature impact on the ductile iron characteristics. It would be also advisable to consider statistical methods that might be helpful in forecasting the ductile iron characteristics with respect to some feature configurations corresponding to chemical composition, heat treatment parameters, etc. Moreover, because of a high percentage of observations with missing information on some explanatory variables, an adequate methodology for data imputation in this context would be also highly recommended.

REFERENCES

Biernacki, R., Kozłowski, J., Myszka, D., Perzyk, M., 2006, Prediction of Properties of Austempered Ductile Iron Assisted by Artificial Neural Network, *Materials Science,* 12.

Bradenberg, K. R., Lee, I., Maxwell, D., Newman, P., 2002, Independent Trailer Suspension Utilizing Unique ADI Bracket, *SAE Technical Paper*, 2002-01-0674.

Fraś, E., Górny, M., 2010,Thin wall ductile and austempered iron castings, *Archives of Foundry Engineering*, 10, 5-10.

Guzik, E., Kapturkiewicz, W., Lelito, J., 2000, The methodology of ausferritic ductile iron International Scientific Conference „Austempered Ductile Iron", Cracow, I/11.

Guzik, E., 2006, Some selected problems concerning the formation of microstructure and mechanical properties of ausferritic ductile iron, *Archives of Foundry*, 6, 33-42, (in Polish).

Kochański, A., Kozłowski, J., Kłębczyk, M., Perzyński, P., 2010, Modelling of austempered ductile iron properties using data base prepared with methodology for data preparation, (in Polish), *Polish Metallurgy 2006 - 2010*, The Committee on Metallurgy of the Polish Academy of Sciences, ed. K. Świątkowski, 2010.

Kochański, A., Perzyk, M., Kłębczyk, M., 2012, Knowledge in imperfect data, in: Advances in Knowledge Representation, ed.: Carlos Ramirez Gutiérrez, Publisher: InTech, Wien, 2012.

Kochański, A., Soroczyński, A., Kozłowski, J., 2013, Applying Rough Set Theory for the Modelling of Austempered Ductile Iron Properties, *Archives of Foundry Engineering*, 13/2, 70-73.

Kochański, A., Krzyńska, A., Radziszewski, T., 2014, Highsilicone Austempered Ductile Iron, *Archives of Foundry Engineering*, 14, 55-58.

Krzyńska, A., Kochański, A., 2014, Properties and Structure of High-Silicone Austempered Ductile Iron, *Archives of Foundry Engineering*, 14, 91-94.

Laino, S., Sikora, J., Dommarco, R. C., 2011, Advances in the Development of Carbidic ADI, *Key Engineering Materials*, 457, 187-192.

Perzyk, M., Kochański, A., 2001, Prediction of ductile cast iron quality by artificial neural networks, *Journal of Materials Processing Technology*, 109, 305-307.

Raghavendra, H., Bhat, K.L., Rajendra Udup, K., Rajath Hegde, M.M., 2010, Grinding Wear Behavior of Stepped Austempered Ductile Iron as Media Material During Comminution of Iron Ore in Ball Mills, International Conference on Advances in Materials and Processing Technologies, AMPT, AIP Conference Proceedings, 1315, 1, 1341-1346.

Seaton, P.B., Xiao-Ming, L., 2002, An ADI Alternative for a Heavy Duty Truck Lower Control Arm, American Foundry Society, Louisville Kentucky, USA.

Yescas, M.A., Bhadeshia, H.K.D.H., MacKay, D.J., 2001, Estimation of the amount of retained austenite in austempered ductile irons using neural networks, *Materials Science and Engineering,* 311, 162-173.

MODELOWANIE WŁASNOŚCI ŻELIWA SFEROIDALNEGO AUSFERRYTYCZNEGO Z UŻYCIEM WIELKOŚCI DYSKRETNYCH

Streszczenie

Żeliwo sferoidalne ausferrytyczne jest doskonałym materiałem konstrukcyjnym. Cechuje się ono wysoką wytrzymałością na rozciąganie zachowując relatywnie duże wydłużenie lub przy wysokim wydłużeniu nadal oferuje dobrą wytrzymałość. Stały wzrost zainteresowania tym materiałem sprawia, że konieczne staje się opracowanie wiarygodnych modeli pozwalających na kontrolowanie procesu produkcji w warunkach odlewni. W pracy podjęto udaną próbę nowego podejścia do modelowania własności żeliwa ausferrytycznego. Dotychczasowe rozwiązania zakładały zastosowanie w budowanych modelach atrybutów ciągłych. Zaproponowane w badaniach rozwiązanie bazuje na wykorzystaniu do modelowania zdyskretyzowanych sygnałów wejściowych.

Do modelowania użyto zbioru danych obejmującego ponad 1400 wytopów. Wybrane do budowania modelu sygnały wejściowe (parametry procesu) zdyskretyzowano zgodnie z wiedzą i dotychczasową praktyką przemysłową. Wyniki eksperymentu potwierdziły możliwość praktycznego wykorzystania modelu bazującego na wielkościach dyskretnych. W podsumowaniu wskazano możliwości poprawy jakości otrzymanego modelu.

Received: October 7, 2014
Received in a revised form: November 2, 2014
Accepted: November 12, 2014