www.czasopisma.pan.pl PAN www.journals.pan.pl

ARCHIVES
of
FOUNDRY ENGINEERING

DOI: 10.2478/afe-2014-0039

Published quarterly as the organ of the Foundry Commission of the Polish Academy of Sciences

DE GRUYTER OPEN

ISSN (2299-2944)
Volume 14
Issue 2/2014

69 – 72

A Method to Make Classification of the Heat Treatment Processes Performed on Bronze Using Incomplete Knowledge

S. Kluska-Nawarecka [a]*, Z. Górny [a], K. Regulski [b], D. Wilk-Kołodziejczyk[a, b], Z. Jančíková [c], J. David [c]
[a] Foundry Research Institute, Cracow, Poland;
[b] AGH University of Science and Technology, Cracow, Poland;
[c] VŠB – Technical University of Ostrava, Ostrava-Poruba, Czech Republic;
*Corresponding author. E-mail address: stanislawa.nawarecka@iod.krakow.pl

Received 17.03.2014; accepted in revised form 30.03.2014

Abstract

The article describes the problem of selection of heat treatment parameters to obtain the required mechanical properties in heat- treated bronzes. A methodology for the construction of a classification model based on rough set theory is presented. A model of this type allows the construction of inference rules also in the case when our knowledge of the existing phenomena is incomplete, and this is situation commonly encountered when new materials enter the market. In the case of new test materials, such as the grade of bronze described in this article, we still lack full knowledge and the choice of heat treatment parameters is based on a fragmentary knowledge resulting from experimental studies. The measurement results can be useful in building of a model, this model, however, cannot be deterministic, but can only approximate the stochastic nature of phenomena. The use of rough set theory allows for efficient inference also in areas that are not yet fully explored.

Keywords: Application of information technology to the foundry industry, Heat treatment, Classification algorithms, Rough sets, Data mining

1. Introduction

The research problem that the authors were expected to solve was a method for the selection of heat treatment parameters applied to the grade of bronze covered by experiments.

The aim of the study was to discover correlations occurring in a set of the experimental data describing the process of heat treatment to build a model allowing an approximation of the unknown variables (tensile strength - R_m; yield strength – $R_{p0.2}$ and elongation - A_5) for results not included in the measurements. Previous studies of the authors in this field enabled creating the approximation models using fuzzy logic for decision trees [1-6].

The results obtained in previous studies allowed performing an analysis, owing to which it became possible to create a set of rules interrelating the choice of the heat treatment path with the expected values of the mechanical properties.

The study began with a statistical analysis of the experimental data. Eighty four samples were available. Two samples were removed from the analysis. In the first case, the reason was the lack of measurements; in the second case, the measurements indicated by the experimenter were in an obvious way deviating from the remaining data in the group. Finally, the analysis covered 82 records.

Due to the high cost of experiments, industrial research often uses small data sets. Studies of materials are based on several samples taken from a single melt. In the reported studies, samples were taken from 7 melts subjected to different modifying treatments.

After the initial selection of features based on the knowledge of researchers, it was decided to choose the following variables:

- Quenching {abs., P}, where abs . means no quenching and P means quenching at 950°C using microjet and water as a cooling agent;
- Tempering {abs., S1, S2}, where abs . means no tempering, S1 - tempering at 350°C for 6h and cooling in air, S2 - tempering at 700°C for 6h and cooling in air.

It was decided to create a supporting variable describing the heat treatment path:

- HT {L, P, PS1, PS2}, where L - as-cast state, P - sample subjected to quenching, PS1 - sample subjected to quenching and tempering at 350°C, PS2 - sample subjected to quenching and solutioning at 700°C.

In this model, the dependent or decision variable will be the HT variable. Based on the results of the statistical analysis, the relationships existing between the heat treatment parameters (HT) and the expected properties R_m, $R_{p0.2}$ and A_5 have been proved.

Due to the qualitative nature of the dependent variable, the stated problem is a typical classification problem, in which the possible values of the classes are acceptable paths of heat treatment {L, P, PS1, PS2} described above. The authors dealt with the problems of classification also in other studies [7-9]. In these studies, they use their previous experience gained in this field of activity.

2. Methodology and the description of experimental data

To solve the problem of classification, in which the decision can be based on an incomplete knowledge only, i.e. incomplete in the sense of incomplete discernibility of objects in terms of the variables, one can use, among others, the theory of rough sets.

The indiscernibility of objects, which is a key concept here, results, among others, from the too scarce information. This information covers the measurement data from the experiments. We can always assume that increasing the number of measurements and increasing the number of samples, as well as eventually increasing the number of controlled parameters will allow us to build a model much more accurate. Such studies, however, cost a lot and increasing the number of controlled parameters will increase the number of measurements in an exponential way.

The increased number of controlled parameters (where the parameter is treated as a variable in the analysis) also increases the space of results. We shall never be able to fully cover with measurements the possible space of results – the space of results is continuous while the number of measurements is highly discreet. This makes the approximation of results necessary. In areas not covered by the measurements, the unknown variables are approximated with the data currently available.

The theory of rough sets is applicable wherever we have limited information about the tested object. In fact, any object (in this case the sample of material) is different, there are no two identical objects. The distinction between them is just a matter of knowing their full description, and in particular the designation of attributes (features, parameters, variables) that distinguish them. Of course not always so detailed description of phenomena is necessary, but if we reduce the accuracy of the description (the number of attributes), this will lead to a situation where some objects will become indiscernible.

The elements about which we have identical information are indiscernible and form the, so-called, elementary sets. About the elements contained in the space of an elementary set we can only say that the values of their attributes are the same as the values of the entire elementary set. Hence it follows that the elementary sets are described by information about the attributes, contrary to the classical set theory, in which the sets are defined by the specification of objects belonging to a given set. This approach allows the rough set theory to be used wherever we are dealing with the attribute-based description of reality.

The rough set is created by a pair of definable sets: lower approximation and upper approximation. The item may belong to both approximations, to none of the approximations, or to an upper approximation only [10-12].

Therefore, the object certainly cannot belong to a rough set (if it does not belong to any of the approximations), it can certainly belong to a rough set (if it belongs to both approximations), or a situation may exist when, based on the features indicated, we cannot rule out that the object can belong to a rough set (upper approximation).

2.1. Test results

The data on the tested materials obtained from the experimental studies included three variables in the form of mechanical properties and one variable describing the process of heat treatment (Table 1).

Table 1.
Descriptive statistics of selected mechanical properties

	n	avg	min	max	s
R_m	82	733.33	330.00	930.00	99.64
$R_{p0.2}$	75	472.08	225.00	805.00	167.94
A_5	74	6.28	0.20	16.90	4.54

The decision variable HT assumed the values of {L,P,PS1,PS2}.

Based on the results of statistical analysis it has been found that the expected values of mechanical properties are dependent on the course of heat treatment. The graph of average quenching-related R_m values in the group of samples quenched P and in the group of samples non-quenched dramatically changes as regards the strength distribution in both these groups. It can be concluded that quenching increases the average strength and decreases the standard deviation – the span of measurements in the group of samples undergoing quenching is more narrow. Quenching also improves the yield strength. On the other hand, samples subjected to quenching reveal lower elongation values. Hence it follows that quenching increases the tensile strength and yield strength but reduces elongation.

Then, the effect of tempering on the measurement results was examined and it has been found that tempering S1 strongly increases the tensile strength while similar effect is not observed for the tempering S2. One can also conclude that tempering S1 reduces elongation, while tempering S2 causes quite the opposite effect - the elongation increases compared with the samples not undergoing this treatment.

Examples of this relationship for the variable R_m are shown in Figure 1.

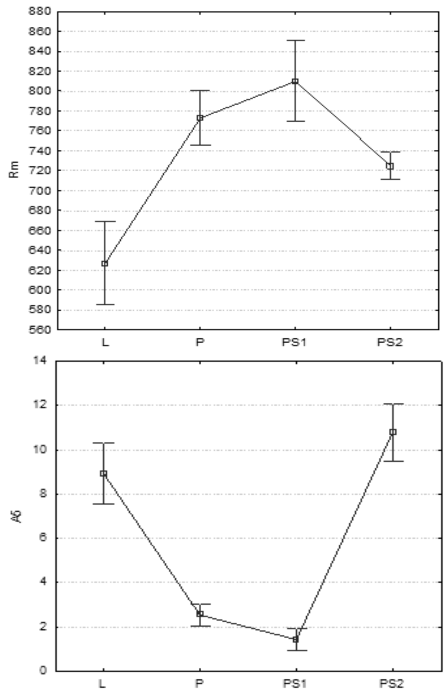

Fig. 1. Average values of R_m and A_5 plotted for the groups of samples undergoing different types of heat treatment

Analysis shows that for the as-cast state (L) and heat treatment PS2, the values of elongation are similar. Also for the heat treatment (P) - quenching and PS2, these groups are indiscernible with respect to elongation. On the other hand, heat treatments P (quenching) and PS1 are indiscernible with respect to both elongation and yield strength. In short we can say that heat treatments P (quenching) and PS1 are indiscernible with respect to mechanical properties. In other words, samples that undergo quenching or quenching combined with tempering at 350°C will have similar mechanical properties.

3. Application of rough set theory

On the basis of the collected experimental data, a table of observations was built. A table of this type is an information system in which the decision variable is HT (heat treatment), while the explanatory variables (conditional attributes) are the mechanical properties R_m, $R_{p0.2}$ and A5. The information system is an aggregate:

$$S = \langle U, A, V, f : U \times A \to V \rangle$$

where:

U – is non-empty and finite set of objects called the universe;

A – is a set of attributes;

V – is a field of attribute $a \in A$;

$f : U \times A \to V$ is an information function such that $\forall a \in A, x \in U, f(a,x) \in V_a$.

If we distinguish in the information system the disjoint sets of conditional attributes and decision attributes, then such a system will be called the decision table, where columns will correspond to attributes and rows - to objects.

The basic operations conducted on rough sets are the same as the operations conducted on standard sets. Additionally, several new concepts are introduced that are not used in the case of standard sets.

For each subset of features, the pairs of objects are in the relation of indiscernibility, if all the attributes from the set B have the same values, which can be written as:

$$IND(B) = \{x_i, x_j \in U : \forall b \in B, f(x_i, b) = f(x_j, b)\}$$

The indiscernibility relation between elements x_i and x_j is written as x_i IND(B) x_j. Each indiscernibility relation divides the set into a family of disjoint subsets called classes of abstraction (equivalence) or elementary sets. The indiscernibility relation describes the phenomenon that the information system is not able to indicate an individual object that meets the values of given attributes under the conditions of uncertainty (the indeterminacy of some attributes not included in the system). The system returns a set of attribute values that match the indicated object and that are an approximation.

3.1. Test results

To generate a set of rules for a given set of data, an RSES packet was used [11]. The preparation of data involved transformation into the required format, and then filling the gaps in measurement data.

The set was divided into two tables: a training set holding 70% of data and a test set (30 % of cases). On the training set, an additional operation of discretisation was performed for a future comparison of continuous and discretised data.

Discretising of variables is done to enable future generalisation of the model - discrete variables allow for greater generalisation of the rules with respect to continuous sets. If a small training set is available, this procedure allows for greater abstraction of the model, and thus avoiding overfitting of the model which might result from a measurement error. The discretisation of a set was carried out along the defined lines of cuts, i.e. the established divisions into the ranges of variation. The variable R_m was divided into six classes, $R_{p0.2}$ into 5 classes, and A_5 into 3 classes. This choice was dictated by the ranges of variation intervals. The divisions are presented in Table 2.

Table 2.
Divisions of attribute variability

Attribute	Size	Description/Cuts
R_m	6	679.5 692.0 702.5 720.0 804.5 819.5
$R_{p0.2}$	5	352.5 376.5 484.5 568.0 707.5
A_5	3	1.7 2.05 12.5

On the basis of discretised variables, a set of 25 rules was created. An example rule has the following form:

(A_5="(2.05,Inf)")=>(HT=PS2[14])

The above can be read as: if the expected elongation is greater than 2.05, then the treatment PS2 should be used. This rule applies to 14 cases from the training set.

On the developed set of rules, a classification with the help of RSES packet was carried out (Figure 2).

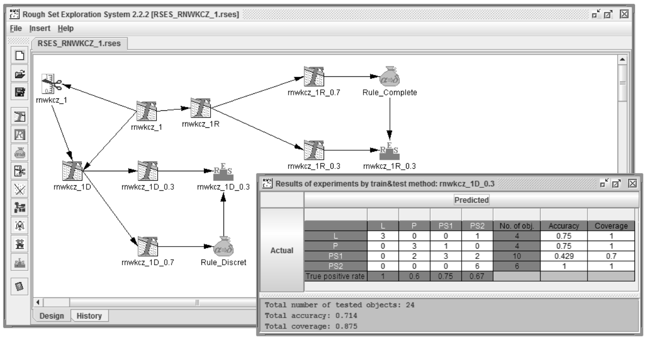

Fig. 2. RSES window

The following results of the classification were obtained.

Table 3.
Classification ratings

	number of tested objects	total accuracy	total coverage
discretised	24	0.714	0.875
generalised	24	0.667	1
completed	25	0.714	0.28

4. Conclusions

The approach using the theory of rough sets in the classification of heat treatment methods applied to the investigated grade of bronze showed that this technique gives satisfactory results. It should be noted that building an inference model in the situation when we have a small number of measurements available and incomplete knowledge about the phenomena occurring in the new tested material is difficult and burdened with large errors. The testing process itself requires dedicating certain number of observations to testing, which means that they will not participate in the model learning process. The rules obtained under these conditions giving 71% efficiency should be considered satisfactory. Applying this methodology, each new experiment can be used to build more rules thereby improving the accuracy of the model.

The presented approach is innovative in the field of materials science and allows for automatic generation of rules which, in turn, allows for further integration and processing of knowledge for the needs of intelligent systems.

Acknowledgements

The work was financed in the framework of the international project No. 820/N-Czechy/2010/0 of 30 November.

References

[1] . Kluska-Nawarecka, S. Górny, Z. Mrzygłód, B. Wilk-Kołodziejczyk D. & Regulski, K. (2010). Methods of development fuzzy logic driven decision-support models in copper alloys processing, *Archives of Foundry Engineering*. vol. 10 spec. iss. 1. 23–28.

[2] Wilk-Kołodziejczyk, D. Regulski, K. Dziaduś-Rudnicka, J. & Kluska-Nawarecka, S. (2012). Overview of activities on the Internet devoted to casting technology, *Archives of Foundry Engineering*. vol. 12 iss. 2, 245–250.

[3] Gorny, Z. Kluska-Nawarecka, S. Wilk-Kolodziejczyk, D. & Regulski, K. (2010). Diagnosis of casting defects using uncertain and incomplete knowledge, *Archives of Metallurgy and Materials.* Volume 55 Issue 3. 827-836.

[4] Nawarecki, E. Kluska-Nawarecka, S. Regulski, K. (2012). Multi-aspect character of the man-computer relationship in a diagnostic-advisory system, Human – computer systems interaction: backgrounds and applications 2, eds. Zdzisław S. Hippe, Juliusz L. Kulikowski, Teresa Mroczek. — Berlin ; Heidelberg : Springer-Verlag.

[5] Mrzygłód, B. & Regulski, K. (2011). Model of knowledge representation about materials in the form of a relational database for CAPCAST system, *Archives of Foundry Engineering*. vol. 11 iss. 3, 81–86.

[6] Spicka, I. & Heger, M. (2013). Utilization Mathematical and Physical Models Derived Therefrom Real-Time Models for the Optimization of Heating Processes; *Archives of Metallurgy and Materials.* Volume 58. Issue 3. 981-985.

[7] Kluska-Nawarecka, S. Wilk-Kolodziejczyk, D. Smolarek-Grzyb, A. & Adrian, A. (2007). Knowledge Representation of Casting Metal Defects by Means of Ontology, *Archives of Foundry Engineering*. vol. 7 iss. 3, 75–78.

[8] David, J. Svec, P. Frischer, R. & Garzinova, R. (2014).The Computer Support of Diagnostics of Circle Crystallizers; *Metalurgija*, 53 (2) 193-196; APR-JUN

[9] David, J. Jancikova, Z. Frischer, R. & Vrozina, M. (2013). Crystallizer's Desks Surface Diagnostics with Usage of Robotic System; *Archives of Metallurgy and Materials* Volume 58. Issue 3. 907-910.

[10] Grzymala-Busse J., & Grzymala-Busse, W. (2007). An experimental comparison of three rough set approaches to missing attribute values, *Transactions on Rough Sets* 6: 31–50.

[11] Bazan, J.G. Szczuka, M.S. Wróblewski, J. (2002). A new version of rough set exploration system. In: James J. Alpigini, James F. Peters, Andrzej Skowron, Ning Zhong, Editors, Third International Conference on Rough Sets and Current Trends in Computing RSCTC, volume 2475, Lecture Notes in Artificial Intelligence, pp. 397-404, Malvern, PA, October 14-16 2002. Springer-Verlag.

[12] Kluska-Nawarecka S., Wilk-Kolodziejczyk D., Regulski, K. & Dobrowolski, G. (2011). Rough Sets Applied to the RoughCast System for Steel Castings, Intelligent Information and Database Systems, ACIIDS 2011, Pt II Volume 6592. 52-61.