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ISSN 0543-5846
METABK 55(4) 821-824 (2016)
UDC – UDK 621.74.04:669.13.001.3:168.2=111

APPLICATION OF DOMINANCE-BASED ROUGH SET APPROACH (DRSA) FOR QUALITY PREDICTION IN A CASTING PROCESS

Received – Primljeno: 2015-11-09
Accepted – Prihvaćeno: 2016-04-20
Preliminary Note – Prethodno priopćenje

The main subject of the paper is a problem of capability assessment of a production process for manufacturing products fulfilling certain requirements. The paper presents theoretical assumptions of the DRSA method for classification of a process state based on so-called process state measures (e.g. process parameters, diagnostic signals, events). In the paper, results of application of the proposed methodology for assessment of capability of the nodular cast iron casting process are presented.

Key words: casting process, cast iron, classification, DRSA method, methodology

INTRODUCTION

Assessment and supervision are important elements in management of manufacturing processes. They allow early detection and reaction to any undesired change that could lead to manufacturing a product incompatible with defined requirements.

In practice, assessment of a manufacturing process requires using a relationship model between supervised output values of a process and its parameters.

For the casting processes, finding these relations is often difficult or even impossible. This is a result of a high level of complexity of a process and a high number of parameters and factors which may influence its course. This is why assessment and supervision of the casting processes are often performed with the use of empirical models developed through data mining methods [1-6].

Depending on the character of the dependent variable, these models (and, consequently, methods) can be divided based on regression and classification [7, 8]. The first group allows prognosis or estimation of numerical value of the dependent variable, while the second allows assignment of an object (a case) to a given class of this variable (e.g. bad, good, average). In both cases, building a model is conducted based on the process parameter values.

The DRSA method [9, 10] is a classification method based on rough set theory, immune to lacks and incoherence of data, resulting in rules clearly shaped and understood for the user. In this method, the discernibility relation (used by classical rough set theory) was replaced by the dominance relation.

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In the paper, the authors present consecutive stages of creation of model of a nodular cast iron casting process assessment, based on the DRSA method. In Figure 1, subsequent stages of its building are presented.

The first step is gathering data in the form of records (cases) that contain values of measured or observed process features.

Consequently the data is prepared for the analysis and specific conditional and decisive attributes are distinguished. An expert determines their preferential directions, then a case set is divided into teaching, test and validation sets.

In the third step, based on the teaching set, a rule model of the process is generated and tested on the test set. In turn validation set is used for iterative improvement, until obtaining a final model. In the validation process, values of the sensitivity (capability of a classifier to recognize a given class if an object really belongs to this class) and precision (measures of reliability of the classification decision) indices are used as criteria for the model assessment.

In the second and third stages, an important role is played by a field expert, who participates, among other things, in determination of preferential directions of attributes and in the model assessment.

EXPERIMENTAL WORK

Studies on possibility of application of the DRSA method for assessment of a nodular cast iron casting process were conducted in one Polish foundry. Influence of the melting process (chemical composition of melt, physical properties of liquid metal and cooling rate) on mechanical properties of a casting was an object of analysis. Among available factors, contents of 9 elements in the melt, which are: carbon, silicon, manganese, phosphorus, sulfur, chrome, nickel, copper and

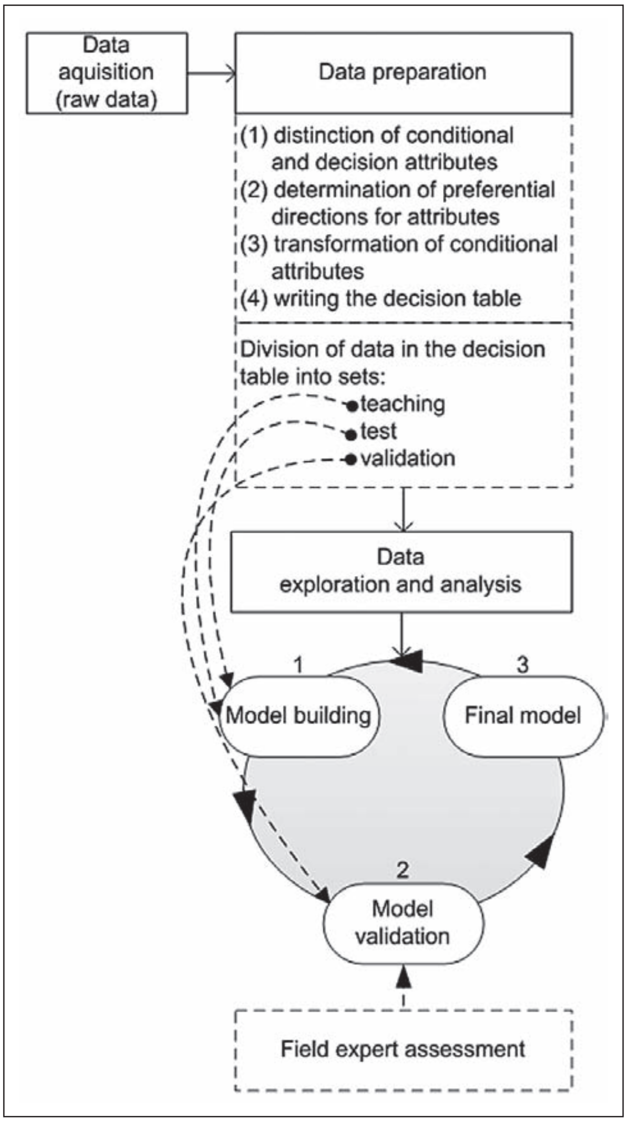

Figure 1 Stages of building a casting process classifier using DRSA

magnesium (C, Si, Mn, P, S, Cr, Ni, Cu, Mg), were acknowledged by an expert as a decisive factor. Evaluation of a nodular cast iron quality was based upon measurement of hardness (HB designation).

The following charge materials were used for melting:

– low-alloyed foundry pig iron – 20 ÷ 30 %;
– cast iron process scrap, added to the furnace as composition supplement;
– iron scrap, usually of unknown composition, forming 10 ÷ 20 % of the charge.

After melting the charge, the metal was kept at ~ 1 400 °C. After full melting, chemical composition of the melt was measured. Recording of percentage contents of particular elements was conducted using a spectrometer connected to a PC. Next, a spheroidizer was supplied into the bottom of a ladle; its quantity was dependent on the alloy planned to obtain and a temperature of a liquid alloy. For the cast iron types of increased hardness, an additive in the form of pure copper or a modifier was added. During the melting process, while feeding the metal to the ladle for spheroidization and in the

Table 1 **Sample data for nodular cast iron melting**

	Cast No.				
Feature /%	1	2	3	4	…
C	3,67	3,78	3,64	3,8	…
Mn	0,32	0,11	0,42	0,16	…
Si	2,35	2,37	2,2	2,55	…
P	0,04	0,05	0,05	0,04	…
S	0,02	0,01	0,01	0,01	…
Cr	0,06	0,02	0,06	0,02	…
Ni	0,04	0,01	0,03	0,01	…
Cu	0,42	0,04	0,15	0,05	…
Mg	0,054	0,036	0,041	0,038	…
Hardness/HB	163	159	192	255	…

ladle for pouring, the temperature was measured using an immersive thermocouple, in the measuring range of 600 ÷ 1 800 °C (measuring accuracy equal to ± 0,1 %). The conducted studies resulted in a set of data containing 866 full records (with contents of 9 basic melt components). A fragment of the data set is presented in Table 1.

The data collected from the castings is characterized by the following values:

– chemical composition of the nodular iron: 3,47 ÷ 4,00 % C; 1,90 ÷ 2,98 % Si; 0,09 ÷ 0,42 % Mn; 0,03 ÷ 0,08 % P; 0,005 ÷ 0,03 % S; 0,01 ÷ 0,12 % Cr; 0,00 ÷ 0,07 % Ni; 0,013 ÷ 0,70 % Cu; 0, 015 ÷ 0,065 % Mg (in the vast majority of melts, the Mg content was > 0,035 %);
– the content of aluminum, titanium, tin and molybdenum are within the ranges of 0,015 ± 0,005 %;
– process parameters: spheroidization temperature 1 480 ÷ 1 525 °C, pouring temperature 1 350 ÷ 1 500 °C, spheroidization time: 1´20´´ ÷ 3´30´´.

Hardness (HB) was considered the main aspect (criterion) for assessing the quality of the casting process. Hardness of the obtained cast iron varied in the range of 152 ÷ 311 [HB]. Such a wide range of values resulted from the class of the nodular cast iron castings produced in the foundry: 400/18, 500/07 and 500/07 with increased hardness (an obligation imposed by the customer). All tests were carried out on separately cast Y2 samples (according to A842 ASTM Standard).

To obtain a rule model of the cast iron casting process, the data was prepared for analysis according to the steps presented in Figure 1 and resulted in a case table. Criteria for assessing the quality of the iron casting process were placed in Table 2. All calculations related to induction of the decision rules and analysis and verification of the rules were conducted using the aMOPS program (acronym from the Polish name for “adaptive Methods of Process State Assessment”), developed in the scope of a research project managed by Kujawinska. Analysis and exploration of data and assessment of a set of generated rules was conducted iteratively, to obtain a model of satisfying predictive capabilities and acceptable by the field expert. For induction of rules out of data contained in the decision table, the VC-DomLEM algo-

Table 2 **Criteria for assessing the quality of the iron casting process**

Assessment criterion	Hardness (HB)		
Description	Hardness class		
Decision classes	{1,2,3}		
Description of decision class	1 low	2 medium	3 high
Principle of class assignment	HB < 175	175 ≤ HB < 210	HB ≥ 210

rithm (Rule induction algorithm for variable consistency rough set approaches) was used and implemented in the aMOPS software.

The role of the field expert on the stage of the model assessment consisted of acceptance or rejection of a given set of rules as a final model. These decisions were made primarily based on estimated predictive capabilities of the model, but also based on other properties of the obtained rules (including knowledge about the process represented by them) and practical knowledge about the casting process and real conditions of its realization.

Because effectiveness of classification of new cases by the model with application of an attribute set containing 9 alloying elements was not satisfying, the considered set of conditional attributes was limited to a subset of attributes indicated by the field expert. This subset contained 4 elements: Mn, Si, Ni, Cu, which, in the expert's opinion, have the biggest influence on microstructure and hardness of nodular cast iron. The results of analyses presented below apply to the limited set of attributes.

The final set of decision rules comprises of 125 reliable decision rules. The rules have a form of logical expressions, which represent the process knowledge in an open way and have a capability to explain the proposed decisions. Because of the syntax of the DRSA method, these rules are written in the form of: "*at least...*" (designation: <=) or "*at most...*" (designation: >=). An exemplary set of rules is presented in Table 3. The longest rule contained all 4 elements.

Stage of validation of the set of rules generated out of the data of the casting process (the model assessment stage) consisted of a formal evaluation of effectiveness of new case classification by this set of rules (by a test of 10-fold cross stratified validation, general accuracy

Table 3 **Exemplary rules**

Rules
If Si <= 2,18 and Ni >= 0,02 Then HB >= 3
If Ni >= 0,05 and Cu >= 0,21 Then HB >= 3
If Mn >= 0,35 and Si >= 2,3 Then HB >= 2
If Si >= 2,21 and Cu >= 0,35 Then HB >= 2
If Si >= 2,64 and Cu <= 0,08 and Cu >= 0,04 Then HB <= 1
If Mn <= 0,1 and Si >= 2,47 Then HB <= 1
If Mn <= 0,15 and Si <= 2,41 and Ni >= 0,02 Then HB <= 1
If Si <= 2,55 and Cu <= 0,05 Then HB <= 2
If Mn <= 0,17 and Si <= 2,49 and Cu <= 0,25 Then HB <= 2
....

Table 4 **Summary of results of 10-fold cross validation test for the casting hardness model, obtained using 4 alloying elements**

Classification result	Averaged number of cases in relation to cardinality of the test set / %		Averaged sensitivity	Averaged precision
Correct	n_c/n	77,6	1: 0,95 2: 0,6 3: 0,56	1: 0,88 2: 0,66 3: 0,6
Incorrect	n_u/n	22,4		
Designations: n_c – number of cases classified correctly n_u – number of cases classified incorrectly n – number of all cases				

of classification and measures of sensitivity and precision were assessed – Table 4) and verification of the rule set and its properties conducted by the field expert.

Accuracy of classification of the obtained model is approximately 78 %. It expresses a number of correctly classified cases in relation to cardinality (size) of the validation set. In contrast, the classification results indicate weaker recognizability of the 2nd and 3rd classes. In the analyzed set, this is a result of lower size of these classes.

CONCLUSIONS

The developed rule model of dependence between chemical composition of a melt and hardness of a casting may be a base of an expert system for assessment and diagnostics of its new realizations and forecasting.

The model of assessment of a nodular cast iron casting process obtained by the authors is characterized by a satisfying level of classification accuracy (78 %), sensitivity and coherence for the particular quality classes. It indicates that it is possible to apply it in practice for the analyzed process.

The authors recommend using the DRSA method for complex processes such as casting processes. It ensures a solution to one of the most difficult problems when building a model, which is consideration of an expert's knowledge. Moreover, the model assessment by an expert is less "formal" than assessment using the computer-based tools; often the fact that it is a separate stage of the procedure is not visible. An expert accompanies the data analysis process and supports and advises on its different stages. The field expert played a decisive role in the process of selection of a set of attributes used for rule induction, thereby directing the process of the knowledge discovery.

In the proposed approach, the knowledge is obtained out of data supplied in the form of examples – successive process realizations. This method is immune to lacks and incoherence of data. As opposed to other data mining methods used for classification, its rules are clearly shaped and understood for the user. Results of data analysis using the DRSA method may be also used for minimizing a set of features describing the process, as well as for its optimization.

Acknowledgments

The presented results derive from a scientific statutory research conducted by Poznan University of Technology (DS 02/23/ DSPB/7605), Poland, granted by the Polish Ministry of Science and Higher Education from the financial means in 2014.

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Note: The responsible translator for English language is: Matthew Hohn, Exact English, Poznan, Poland