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Methods of Computational Intelligence in the Context of Quality Assurance in Foundry Products

**G. Rojek [a], K. Regulski [a], D. Wilk-Kołodziejczyk [a,b]*, S. Kluska - Nawarecka [b],
K. Jaśkowiec [b], A. Smolarek-Grzyb [a]**

[a] AGH – University of Science and Technology, Al. Mickiewicza 30, 30-059 Krakow, Poland
[b] Foundry Research Institute, Cracow, Poland;
Corresponding author: E-mail address: dwilk@agh.edu.pl

Abstract

One way to ensure the required technical characteristics of castings is the strict control of production parameters affecting the quality of the finished products. If the production process is improperly configured, the resulting defects in castings lead to huge losses. Therefore, from the point of view of economics, it is advisable to use the methods of computational intelligence in the field of quality assurance and adjustment of parameters of future production. At the same time, the development of knowledge in the field of metallurgy, aimed to raise the technical level and efficiency of the manufacture of foundry products, should be followed by the development of information systems to support production processes in order to improve their effectiveness and compliance with the increasingly more stringent requirements of ergonomics, occupational safety, environmental protection and quality. This article is a presentation of artificial intelligence methods used in practical applications related to quality assurance. The problem of control of the production process involves the use of tools such as the induction of decision trees, fuzzy logic, rough set theory, artificial neural networks or case-based reasoning.

Keywords: Application of Information Technology to the Foundry Industry, Quality Management, Casting Defects, Computational Intelligence, Artificial Intelligence

1. Introduction

A key aspect determining the effectiveness of information systems supporting the implementation of production processes is the competent organization for the flow of information and the ability to integrate data from distributed sources. Previous work in this area mainly included the creation of modules for individual problems, while collective treatment of the issues of computational intelligence in foundry production have not yet been fully developed in the previous embodiments, although their broader use can lead to enrichment of functionality and decision-related advantages of the constructed solutions. One way to ensure the required technical characteristics of castings is the strict control of production parameters and elimination of defective products, which lead to huge losses, if the production process is improperly configured. Therefore, a more economical method of quality assurance is constant, ongoing monitoring of the parameters of the production process and correction of various factors when the formation of defects is diagnosed or deviations from the expected properties are traced. At the same time, the development of knowledge in the field of metallurgy, aimed to

raise the technical level and the efficiency of production of machinery, vehicles, tools, mechanical devices, etc. should be followed by the development of information systems to support production processes in order to improve their efficiency [1]. Technological operations making up the manufacturing process of metal products have their own specifications and characteristic types of the parameters that are controlled within each process step. The nature of this data determines the formalisms possible to use in the area of mathematics, statistics and computational intelligence that can help in monitoring, control and decision making [3]. The aim of this article is to present a series of the currently used methods of computational intelligence with particular regard to the possibility of their application in specific examples of problems.

2. Problems related to compliance with technical conditions

The quality of castings depends, among others, on the content of harmful contaminants in the form of trace elements, which in addition to phosphorus, sulphur, arsenic, tin and antimony, also include hydrogen, nitrogen and oxygen. Gases deteriorate technological properties of metal, and especially have a strong negative impact on the majority of performance characteristics of the castings. Too high gas content in the melt is a cause of defects on the surface of casting and in its interior. To ensure the appropriate quality level of production, it is necessary to control the quality and technological parameters of all raw materials used in production. The quality of castings is influenced by a number of parameters, which are important at different stages of the production process. For example, defects that may arise from the improper performance characteristics of moulding and core sands include pinholes caused by the presence of hydrogen, sand inclusions, deformation, gas content, fractures, and shape defects. Selection of an appropriate moulding material is dictated by the properties that determine its suitability for making the casting characterized by the required technological properties. In other words, usually the cheapest moulding sand is used (and binders appropriate for this sand) that can provide the adequate required technological properties. In the event of failure to satisfy the required parameters, the risk of developing a casting defect can be expected. Due care should also be taken to eliminate the undesired chemical matters penetrating from the mould to the casting (oxides, nitrides, oxysulphides, oxynitrides, carbonitrides, and finally water vapour). Possible defects formed during melting include misruns, slag inclusions, hot tears (in the case of too high temperature), gas content, wrong chemical composition, and pinholes. Finding specific parameters responsible for the formation of a given defect depends primarily on the type of defect which prevails in a foundry shop. All stages of the production process of castings have a significant impact on the quality of the final product, and therefore there is no single stage in the production process that could be considered most responsible. In various stages essential for the formation of defects there are different parameters that should be monitored (Table 1). Some process steps go beyond the standard control of process parameters (design and construction of foundry patterns

and moulds). What is needed for these tasks is knowledge of the literature and simulation, which requires completely different methods of computation than the numerical data from the measurements [2]. The aim of the studies of computational intelligence in the foundry industry is to provide support for the technologist who is in charge of the process. The relevant tools should provide the necessary information about the course of the melting process, and also allow the execution of expertise - the assessment of the correctness of the process and procedures in case of any deviations from the correct condition. An assessment of this type must be based on the knowledge and experience of experts, and therefore the role of the information tools is to facilitate the implementation of this knowledge into the knowledge base used by the information modules.

When the user faces the diagnosed irregularity, it is necessary to provide a feedback between the input and output parameters of the process and thorough knowledge of relationships between various parameters and the effect of their changes on properties of the final product. Capturing such relationships is possible owing to the knowledge of experts, but also owing to the automatic algorithms of knowledge acquisition (e.g. decision trees).

Table 1. Key factors affecting the occurrence of defects

I. The design of pattern, mould and gating system
– mould compaction technique and squeeze pressure
– permeability, grain size, moisture content, compactability, refractoriness, friability, composition and moulding material
– parameters (thickness, composition, refractoriness) of protective coating
– pattern design parameters
– parameters of mould and gating system, filters (if any) (composition and structure)
II. Parameters of the charge and melt
– chemical composition of the charge material and surface condition
– castability of molten metal
– melt oxidation and oxygen activity
– chemical composition of the melt
– content of non-metallic inclusions (oxygen, nitrogen, hydrogen, etc.)
III. Mould pouring and process parameters
– pouring, mould and melt temperature
– the amount of metal in the ladle and the height of pouring
– flow rate and pouring rate
– the duration of individual phases of the process
– parameters of gas atmosphere in the furnace during annealing
– parameters of the oxygen refining, blowing and argon shielding of the stream of molten metal during tapping
– casting cooling and solidification rate

3. Methods of computational intelligence in casting production

From the foregoing it can be concluded that the tasks of computational intelligence and artificial intelligence in support of

foundry processes are diverse and depend on the tested stage of the process. In most cases they (1) enable monitoring the condition of parameters affecting the formation of casting defects and, depending on the received signals, decide on the necessity of intervention in the process; (2) enable formalization of domain knowledge to create models of inference supporting the decision-making process; (3) enable automatic acquisition of knowledge (in the form of rules) concerning the phenomena and relationships between process parameters. For each of these tasks, appropriate computational techniques are chosen and adapted. In the next part of this article, each method will be discussed and illustrated with appropriate examples.

3.1. Induction of decision trees

Induction of decision trees is a process that requires extensive sets of training data. This data may come from experiments or measurements taken during the process. The main tasks of decision trees are: (1) classification in the case of discrete dependent variable, or (2) regression, when the dependent variable is continuous. Algorithms of the construction of trees are a very popular way to discover the relationships between the parameters describing various phenomena, so it is possible to discover correlations, which the technologist may not notice [4,5]. Their popularity stems largely from the fact that they can operate equally well on the numerical data (such as regression models, neural networks and support vector method) and qualitative variables, even of the linguistic nature [6]. The decision trees allow us to build models of phenomena that can not be described in a deterministic manner, and the nature of phenomena does not have to be linear. The result of the algorithms operation are trees, which are graphical form of decision rules, and are relatively easy to interpret by man, in contrast to the above methods. The specificity of algorithms of the induction of decision trees allows for an assessment of the impact of various parameters on the studied phenomena. In this way they also fulfil the task of the sensitivity analysis. By manipulating large data sets, the trees make generalizations of the relationships, which are insensitive to single outliers and deviations (noise).

The most popular algorithms for induction of decision trees, i.e. CaRT (Classification and Regression Trees) and CHAID (Chi-squared Automatic Interaction Detector) described in [7,8], allow building the trees of both classification and regression, depending on whether the dependent variable is continuous or discrete. Applied in production processes they allow, among others, control of the signals in continuous processes, such as the production of connecting elements [9], where the class of product is estimated based on the heat treatment parameters. Another example is the production of rolled elements, where the analysis by means of CaRT algorithm enables evaluating the impact of process parameters along with their optimization [10].

In all cases, the use of decision trees leads to the rules, which can constitute the knowledge base needed in automatic evaluation and control of the production process (Fig.1).
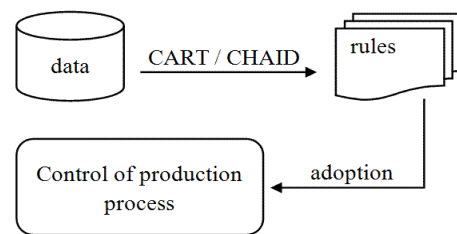

Fig. 1. Schematic representation of the use of decision trees

3.2. Fuzzy logic

Building a knowledge base based on fuzzy logic implies the need to have expert knowledge that helps in the formalization of rules operating on fuzzy sets [11]. However, there are tools for data-based machine learning, such as the popular ANFIS, which is an expansion of Matlab package. Fuzzy logic has already gained a well-deserved popularity in issues of process control. It is used in advanced devices like cars, washing machines, and smartphones, and also in simple cylinders. Fuzzy models allow reducing the number of rules and a smooth transition in the areas of membership, which allows building models of reasoning similar to the reasoning carried out by man [12]. In the field of metallurgy, fuzzy models are used not only in process control but also in materials science to achieve automation in making multiple decisions. An example might be the use of fuzzy inference model to study the microstructure of aluminium alloys [13].

3.3. Rough set theory

Problems of classification, in which decisions about the class of dependent variable are based on values of signals can be reduced to a decision table. In practical terms, a table like this is nothing else but a way to represent the decision rules, where each conditional attribute (signal) is a prerequisite, and decision attribute is a conclusion of the rule. The generation of decision tables is included in the field of artificial intelligence and tools of this type are among the methods of machine learning. One of them is rough set theory [14], particularly useful when the signals on which the decision is based have a discrete form. We can use this tool to solve the problem of classification, in which the decision can only be based on incomplete knowledge - incomplete in the sense of incomplete discernibility of objects in terms of the values of the pertinent variables, or in other words - when the signals may not differ in the attribute values, while having different values of decision variable. The indiscernibility of objects which is a key concept here results, among others, from the fact that too little information is available. Rough set theory applies in all those cases where we have limited information about the examined object. The rough set is formed by a pair of sets definable in lower approximation and upper approximation. The item may belong to both approximations, to none of the approximations, or only to the upper approximation [15]. Accordingly, the object may certainly not belong to the rough set (if it does not belong to any of the approximations), it may

certainly belong to a rough set (if it belongs to both approximations), or the situation may occur when, based on the indicated features, we can not rule out the object membership in a rough set (upper approximation). The approach using rough set theory has shown that, applied to the classification of various methods of the heat treatment of bronze alloy [16,17], this technique gives satisfactory results. It should be noted that building a model of inference for new test materials in a situation where we have only a small number of measurements, as well as incomplete knowledge about the phenomena is difficult and highly biased. The very process of testing the model requires the dedication of a number of follow-up tests, which means that they do not participate in the model learning process.

3.4. Artificial neural networks

Possible applications of artificial neural networks to control manufacturing parameters of foundry products are seen through the prism of prediction, which is one of the main possibilities offered by this group of computational intelligence methods. Prediction allows us to foresee the quality parameters of finished products depending on the value of individual production parameters. To obtain such a tool it is required to subject an ANN (artificial neural network) to the so-called training process (Fig. 2). In the case of MLP type (Multilayer Perceptrons) networks, backpropagation algorithm can be used as the one which allows us to obtain a network mapping relationships related to the training data. However, the process of network training demands attention and control of the developer - too small amount of training data can contribute to the misprediction burdened with very serious error. This is the basic problem encountered in the use of neural networks in manufacturing enterprises that do not have large data resources.
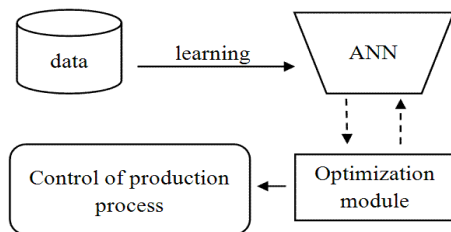

Fig. 2. Schematic representation of typical application of artificial neural network (ANN) together with the optimization module

Assuming, however, the opportunity to train the network allowing for the prediction of quality parameters of finished products, one should take into account the need to use an additional module, whose task will be optimization of control process. Optimization module will be using the prediction of quality parameters for potential (technically possible) manufacturing parameters and returning such values of the manufacturing parameters, for which the quality parameters of finished products take optimum values. The design of the optimization module may require the use of additional methods of artificial intelligence (e.g. genetic algorithms), which will allow determining the best solution from the point of view of specific quality criteria. More accurate

description of this methodology can be found in [18,19]. In foundry issues, quite successfully are used the neural networks that enable, for example, determining the value of future mechanical properties of the material based on the parameters of the manufacturing process [20].

3.5. Case-based reasoning

The main paradigm of CBR (Cased-Based Reasoning) is an inference regarding the solution of current problem by (1) the selection of a similar case from the database referred to as the case base, and (2) adaptation of the solution of the chosen case to the characteristics of the problem [21]. CBR methodology also allows saving the data regarding current problem along with the implemented solution in the database, which allows training of the system based on the solutions indicated by this system and their impact on the actual production process. Case-based reasoning has been applied, among others, in supporting the production of copper alloys, as a system advising the user on the selection of relevant process parameters of the alloy manufacture [22], and in the process of lead refining treatment [24]. A diagram displaying the use of CBR methodology in the context of the use of production data and an impact on the control of production process is shown in Figure 3.
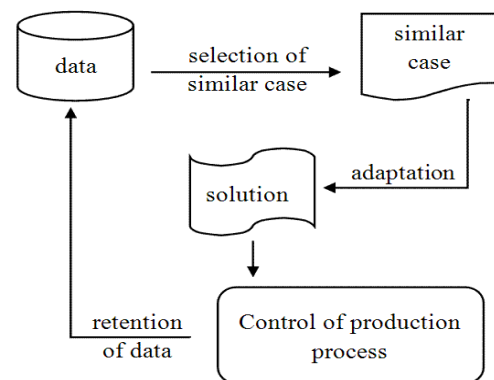

Fig. 3. CBR methodology implementation for support of the manufacturing process control

The implementation of the system based on CBR methodology may involve the problems of establishing a measure of similarity used when selecting the most similar cases. This measure should reflect the similarity in terms of the manufacturing technology, hence so essential for the construction of such a system is cooperation between the team of engineers and programmers. The same problems may arise during implementation of the adaptation phase, although in a large number of applications, this phase can be reduced to the operation of returning the solution being a copy of the solution developed for a most similar case [24]. The efficiency of the system based on the CBR methodology is closely related to the content of case base, which in the case of applications considered in this article involves the data relating to the previously conducted production. In most general terms it can be said that the more data is available, the more detailed

information should be given by the system about the solution of problems specified by the user. Systems of this class are, however, systems learning while in use, which means that the base of cases grows gradually with solving of new problems. Thus the CBR methodology allows for the development of a system supporting the control of production in the context of the quality parameters, even with scarce number of data, while allowing for the addition of relevant data during subsequent use of the system. So this is an approach different to the approaches described within the study of the implementation of an artificial neural network or rules resulting from the application of an algorithm used in creating the decision trees.

4. Conclusions

The methods of computational intelligence described in this study do not cover all the formalisms used in the support of industrial processes. What can still be mentioned is the method of probabilistic classifiers [25,26], or the recently popular method of support vectors [27-30]. Each of these methods has its advantages, but also limitations. The methods described above are a contribution to the overall presentation of artificial intelligence tools in foundries; they also show an attempt to determine the advantages and limitations of each method. The tools presented enable implementation of machine learning, or knowledge acquisition based on the data. For their design, a domain knowledge in varying degrees is required; it is not needed for the induction of decision trees, but it is needed in the case of fuzzy logic. In contrast to CBR, CaRT algorithm is insensitive to outliers, which may allow skipping the noise, but also may result in the lack of accurate assessment in the case of special situations. CaRT algorithm and rough set theory allow generating rules understandable for human, capable of visualization and the use in expert systems. CBR focuses on solving current problems on the basis of similarity to past cases, while fuzzy models are an inference system in itself, although requiring expert knowledge Artificial neural networks can not be interpreted by man and are not suitable for solving problems based on quality variables, but in a situation where we have a large number of numerical data allow building models of approximation much more accurate than other methods. The methods of computational intelligence used in foundry processes allow for (1) an approximation of the unknown values of parameters based on the data from production or experiments; (2) the formalization of rules that are an algorithmic record of the acquired knowledge; (3) building models of inference. Each of them has its limitations, among which there are the following ones: (1) the difficulty in interpretation of the neural networks by humans; (2) the inability to formulate rules of inference for the ANN; (3) the lack of continuity in the area offorecasting with the help of the decision tree (CaRT); (4) the inability to create a single model for several dependent variables in the case of CaRT regression trees; (5) the need to use domain knowledge in the case of fuzzy logic; (6) the low accuracy of the results or the inability to take decisions in new situations with the use of CBR. The individual characteristics of each of the methods allow concluding that the full range of benefits to the user is achieved only by using several algorithms.

Acknowledgements

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