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Introducing Advanced Data Analytics in Perspective of Industry 4.0 in a Die Casting Foundry

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Abstract

The paper presents some aspects of a development project related to Industry 4.0 that was executed at Nemak, a leading manufacturer of the aluminium castings for the automotive industry, in its high pressure die casting foundry in Poland. The developed data analytics system aims at predicting the casting quality basing on the production data. The objective is to use these data for optimizing process parameters to raise the products' quality as well as to improve the productivity. Characterization of the production data including the recorded process parameters and the role of mechanical properties of the castings as the process outputs is presented. The system incorporates advanced data analytics and computation tools based on the analysis of variance (ANOVA) and applying an MS Excel platform. It enables the foundry engineers and operators finding the most efficient process variables to ensure high mechanical properties of the aluminium engine block castings. The main features of the system are explained and illustrated by appropriate graphs. Chances and threats connected with applications of the data-driven modelling in die casting are discussed.

Keywords: Application of information technology to the foundry industry, Mechanical properties, Die casting, Process control, Data analytics

1. Introduction

The 4th industrial revolution, usually referred to as Industry 4.0, became already a reality in many branches of industry, including foundries [1, 2]. It is focused on creating self-teaching, intelligent factory, which will be able to predict the quality of the product and, in the future, even improve it by itself. As the product's quality is a function of process parameters, the on-line collected data may be used in the assurance of final product's quality. Big data analytics and machine learning technologies are now being applied to almost all manufacturing industries, offering new opportunities (see, e.g. [3, 4]).

Among all types of foundries the high pressure die casting foundries are probably the most advanced in the process automation and gathering complete production data, making the basis for Industry 4.0. On the other hand, due to the high number of process variables involved and to the non-synchronization of all process parameters in a unique and integrated process control unit, die casting is perceived as a defect-generating process showing little flexibility to any changes in products' design and in the process evolution [5]. As indicated in an in-depth analysis presented in [6], monitoring and correlating all the main process variables as well as process optimization based on an expert knowledge are the key point in the quality assurance of die castings production.

Currently Nemak's database in its plant in Poland gathers the majority of the process parameters from all high pressure die casting machines resulting in more than 15 000 sets of new data per week. The data cover the most important process parameters, including liquid alloy temperature, injection parameters, die thermo-balance parameters etc. The systems for liquid alloy tracking and more accurate description of cooling circuits flow are being developed. The Nemak 4.0 R&D project, currently carried out in Poland includes two main tasks. One aims at the development of complete systems for recording the process and product parameters. The other task is a development of algorithms capable of predicting the casting quality basing on the historical data, which can be further used for optimal control and adjustments of the process parameters. In the present paper the data analytics system, being the second part of the whole project, is presented.

The key mechanical properties of aluminium die castings are ultimate tensile and yield strengths, elongation and hardness. For each new engine, the customers ask for a higher performance, that means increasing mechanical properties. Besides that, Nemak has started production of the vehicle structure parts such as frame rails, shock towers or tank cover frames. These elements are crucial for the passengers safety, thus the proper development of material's mechanical properties is essential. In order to obtain reliable data, the material properties are tested on the samples cut from the castings. In engine blocks the bearing regions are chosen as the most massive areas with a thickness reaching 20 mm in some products, a real challenge to achieve high mechanical properties. Finding reliable relations between process parameters and the mechanical properties of castings using these limited amounts of data is an important task for engineers.

2. General characteristics of data analytics for casting process control

There are many process and material parameters, i.e. potential input variables, which may affect the mechanical properties of the cast alloy. The first selection has been made by the foundry engineering staff and it covers a wide range of almost all recorded variables related to mechanical and thermal parameters of the casting process, the alloy chemical composition and its heat treatment parameters. Total number of these variables is about 60.

The development of the data analytics system has been divided into three main stages. The first one is the preliminary analysis of the data aimed at detection of the correlations between the input variables; strong correlations would make it possible to reduce the number of the variables worked in the next steps. The goal of the second stage is to identify those variables, which are most significant for obtaining the desired mechanical properties of the cast alloy. This kind of analysis would provide very important information. Firstly, about process parameters which can be used for efficient control of the casting quality, especially in the situations when some of them are 'forced' and 'stiff' (e.g. chemical composition of the alloy) and secondly, supporting the choice of the variables used in the next stage of the project. In the third stage an advanced multivariate data-driven model will be constructed linking the mechanical properties of the cast alloy with process parameters. It can be used as an important aid for anticipated setting optimal process parameters and also process fault diagnostics.

3. Correlations between input variables

Two types of correlation coefficients are computed for all possible pairs of input variables: the widely used linear Pearson and the non-parametric Spearman, which could possibly give more realistic (higher) values for non-linear, but evident, relationships. The most striking finding was that the number of highly intercorrelated process input variables with at least one other variable (absolute values of Pearson or Spearman coefficients above 0.9) was about 25, i.e. almost half of the total number of input variables. A thorough analysis of the observed correlations allowed the authors to identify the following three main kinds of the correlations sources:

1) Physical (natural) correlation, for example between two temperatures measured in adjacent areas of the die or between water flow and its temperature in the same cooling channel. This kind of correlated variables can be easily replaced by one variable, more apparent from the viewpoint of the product quality and suitability for adjustment.
2) Intentional correlations being a result of the operators' or engineering staff actions. They were observed mainly in new developments and should be eliminated in further stages of the project.
3) Coincidental correlations, i.e. resulting from simultaneous occurrences of some values in some time periods. In further project stages they should be avoided but some additional tests may be necessary.

4. Significance analysis of die casting process parameters

As stated in [7], solving many manufacturing problems can be aided by extraction and utilisation of the particular type of information obtained from recorded historical data: relative significances of process variables. Determination of the most significant process parameters can help to perform various types of tasks related to manufacturing, such as detection of root causes of deteriorating product quality. The idea is that the process variables which are found to be the most significant for a given quality parameter, e.g. percent of defective parts, should be regarded as the first candidates of the quality decline. Finding the most significant variables allows to select them as the most efficient process variables in process control. Also, finding the least significant process variables can be valuable. Variations of such variables can be allowed without consequences in product quality, which can lead to reduction of the inspections' costs.

At the current stage of the Nemak 4.0 project the significance analysis of the process input variables is aimed at identification of the most significant ones. They will be subjected to a special attention and will be kept at the values enhancing mechanical properties of the castings. The significant parameters will be also used at the later stages of the project as the input variables for an advanced data-driven model, linking the mechanical properties of the cast alloy (and/or other castings properties) with process parameters, briefly characterized in Chapter 6.

Relative significance of an input variable can be defined in different ways and calculated by various methods, covering various statistical tools and advanced machine learning models [7, 8]. In the present project the one-way analysis of variance (ANOVA) was adopted, being a relatively simple and illustrative non-parametric statistical method. It appeared to be sufficiently reliable and practical for the output variables of the numerical continuous type [7]. It was implemented in a form of a dedicated MS Excel based software featuring automated computations of ANOVA parameters for up to 60 variables, calculations of their relative significances and the estimation of achievable output changes due to the given input changes. In Fig. 1 an exemplary graph shows the selection of statistically significant input variables.

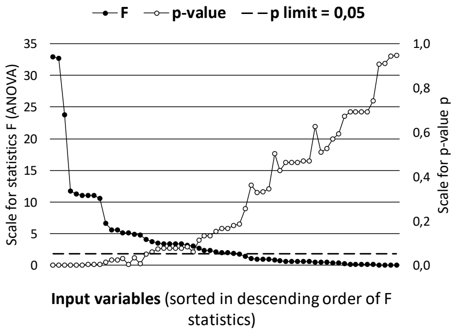

Fig. 1. Example of selection of the statistically significant variables for ultimate tensile strength, based on the ANOVA critical p-value

For the significant variables two parameters are computed, shown in Fig. 2. The first one is the variable's relative significance defined as the current F value divided by the maximum F value among all input variables. This definition is similar to that utilized and assessed in [7]. The second parameter is the estimated achievable output change due to changes of the given input variable, defined further.

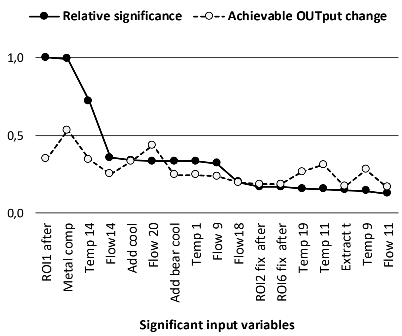

Fig. 2. Example of ANOVA-based parameters calculated for the process input variables being statistically significant for ultimate tensile strength

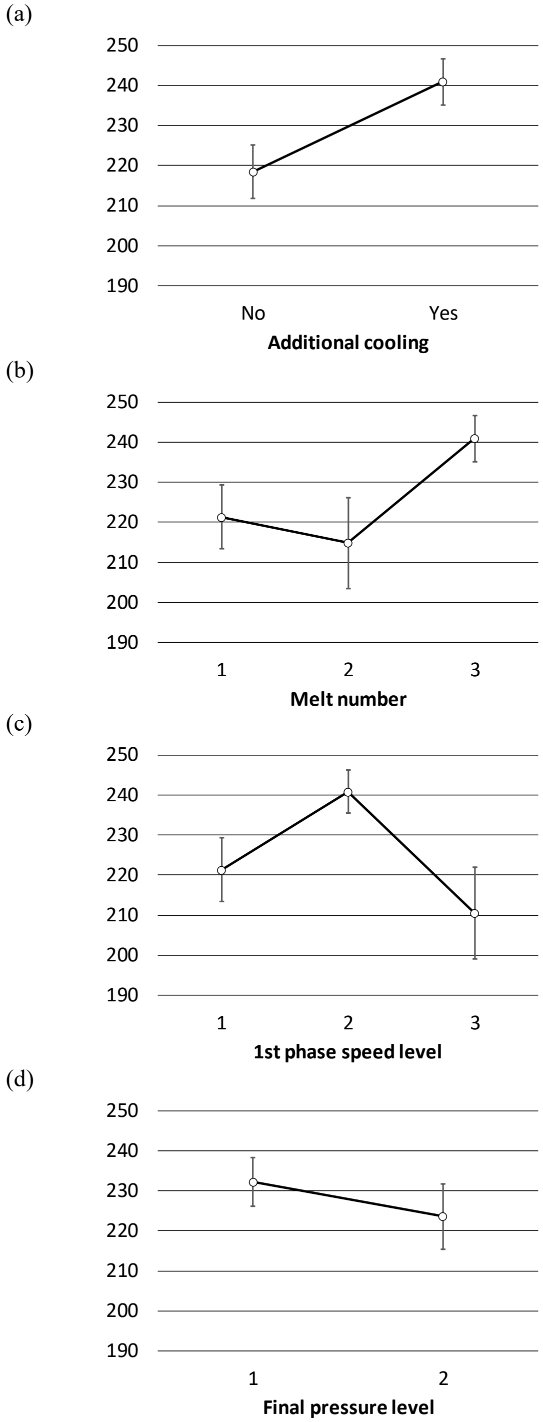

Fig. 3. Examples of ANOVA results showing dependencies of tensile strength on various process parameters; in (a) and (b) are nominal type inputs, in (c) and (d) are continuous type inputs, in (a), (b) and (c) the input variables are statistically significant ($p < 0.0001$), in (d) the input is statistically insignificant ($p = 0.16$)

5. Industrial application of the analysis

The significance analysis was done for various three and four cylinders (I3 and I4) blocks designs. The influence of process parameters on ultimate tensile strength, yield strength as well as elongation has been investigated. An exemplary I4 cylinder block is shown in Fig. 4 with marked bearings area - the section where samples were taken to test the mechanical properties. The parts are cast from the AlSi9Cu3(Fe) aluminium alloy. The considered process parameters included injection parameters such as set point times, plunger velocities and strokes, biscuit height etc. They also included liquid alloy temperature, chemical composition and quality. Last, but not least, influence of die cooling parameters were considered.

The analysis revealed, that properties measured at various bearings (3 bearings considered for an in-line 4 cylinder block, 2 bearings for in-line 3) are affected by different process parameters. This is clear, as the liquid alloy enters the bearings in different condition. For example, the bearings filled with colder alloy (cavities filled at the end) may lead to a lower casting quality.

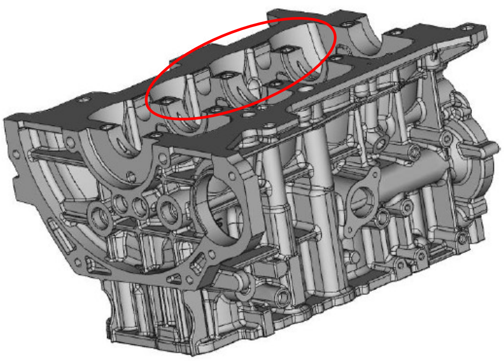

Fig. 4. Exemplary I4 cylinder block with bearings area marked

It has been found, that the 2nd phase and multiplication parameters, such as plunger velocity, times and strokes revealed a statistically significant influence on the material's properties. Process parameters, which influence the alloy's mechanical properties the most, are die cooling circuits flow and cooling agent temperature. This can be attributed directly to solidification conditions, as the microstructure formed during solidification has direct influence on the properties. However, the influence was not found only in the bearings regions (affecting solidification) but also other regions of the cylinder block (left and right sides, bottom part). In this case, the mold filling has to be taken into account. Before the liquid alloy approaches the bearings area, it is transported through the block's walls. If the cooling of such areas is too intense, the alloy approaching bearings area will be cold. This, in turn may result in formation of large shrinkage porosities and other casting defects, significantly reducing material's mechanical properties.

It should be also well understood why other process parameters were found not to have statistically significant influence on the material's properties. It is well known, that the injection parameters, such as 1st and 2nd phases profiles, multiplication delay and pressure, biscuit height and so on are highly important for the final part quality. However, the analysis is done on the serial production. In such case, not only the influence should be considered but also the variability of the parameters. There are two kinds of process parameters that need to be distinguished:

1) Fixed process parameters – the variables, which are set during the product development phase with the optimal values for the process. Their variation in the serial production is affected by other factors only in a minor way. Thus, if a major process defect is not occurring, their variations are negligible for the part quality. These are, amongst others, 1st and 2nd phase profile, applied pressure etc.
2) Dependent parameters – the variables are also set during the product development phase. However, they may be influenced by process environment such as humidity, temperature, number of parts cast in series, etc.

The die thermal balance and the cooling circuit parameters are perfect examples of such variables. They are affected, amongst others, by the ambient temperature or number of parts cast during the production. The conducted analysis revealed, that, for example, temperature of the cooling agent at the output of the circuit is increasing for even an hour after the production start. It indicates, that the filling and solidification conditions may significantly vary.

6. Conclusions and future work

The data-driven advanced model being developed within the project can serve as a key element of a 'virtual operator' and/or 'analytical operator' defined in [9]. The final task of the project will be an advanced data-driven model, linking the mechanical properties of the cast alloy (and/or other castings properties) with process parameters selected as indicated in this paper. It is expected that it would be able to detect complex hidden interrelations between variables, including synergies.

There are many model types within the computational intelligence area (discussed in an accompanying paper [10]). The crucial problem in selecting the appropriate type are the small sizes of data sets containing measured values of mechanical properties, though the values of process parameters are available in the form of automatically recorded, large databases. It seems to be a more general observation that in the era of Industry 4.0 some important limitations due to the physical nature of products and processes may play a significant role and the contrast between Big Data and 'small data' is one of them.

The development of the Industry 4.0 ideas in the foundry practice is not only limited to the proper data analysis, but, in the first stage, description of all process parameters that should be collected. As long as the important variables will be missing, the 4.0 revolution can't take place in a facility. Results of the presented analysis are a good starting point for HPDC foundries, indicating the most significant parameters for the parts casting quality. Further work is still ongoing to evaluate more precisely the influence of individual process parameters. It is expected that the results of Nemak 4.0 project will remarkably improve the stability and predictability of the die casting's production process. It will also become a significant part of the Industry 4.0 framework in the foundry production area.

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