Advanced prediction tools, foundry process control and knowledge management for iron castings

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Abstract

It is well known that the large number of variables that interact during the foundry process bring about many drawbacks. These difficulties are even bigger when we try to predict the behaviour of the process since it is extremely complicated to establish correspondence relationships among the most critical variables on the basis of relating data.

The simulation tools, the control devices and the process management systems used, are very useful but they do not satisfy the stringent demands of the foundry industry. The above mentioned tools work independently and they do not take into account the relationships existing among them.

This research takes into consideration certain IT generic tools that, once adapted to the foundry process and implemented on the basis of specific knowledge, are capable of processing and interrelating a huge amount of data in such a way that they can predict the final quality of the castings, maintaining at the same time the process under controlled conditions.

These tools manage the information coming directly from the foundry plant, what allows to strengthen the process and make a continuous progress by a constant information feedback, helping to improve the own rejection rate levels, even shown in ppm, etc. The fact of developing tools capable of managing all these concepts has been considered a utopia in the foundry process for a long time.

The analytical process used is based on the selection of concrete incidences, parameters and defects. The system assigns them the potential causes considered more probable by the classic knowledge and later on, they are selected and given priority according to objective criteria.

The conclusions reached are based on applications and verifications carried out on different foundries. They have allowed us not only to validate the correct functioning of the system but also to verify its efficiency according to the success rate. It is possible to 'master the process', reduce the variability rate, minimise incidences and manage efficiently the own knowledge by using the data existing in each foundry and by integrating the different prediction and control tools.

Introduction

Foundry technology can be considered widely extended since almost all equipment, vehicles and machines include parts produced through this technological process. Traditionally the automotive industry has been implementing more and more strict requirements for cast components and nowadays other sectors are joining this tendency towards new demands. Clear examples can be found in the railway, turbines, motors and wind energy castings.

The complexity of the foundry process, the great amount of interacting variables, and the higher and higher customer requirements make the final outcome (the quality of the parts) to have quite often an uncertain result.

Besides, we must take into consideration the need for technical knowledge and its own management. Knowledge is a key element for the competitiveness level within the manufacturing industries and without any doubt, this is even more obvious in a foundry.

The foundry industry uses different analytical tools (chemical composition, thermal analysis, design of feeding and filling systems, etc) in order to keep the process under control, improve the final quality of the castings and reduce the rejection rates. The daily foundry practice shows that all of them, even when necessary, are insufficient to fulfil the increasing market demands.

Additional developments have been introduced into the process simulation tools that without any discussion, provide valuable information.

All the process controls along with the different simulation tools work separately, having no links that might lead to a global process evaluation.

In this circumstance it is extraordinarily difficult to explain many of the problems or incidences that arise during the production process.

The most advanced foundries are fully aware that, for maintaining a competitive position in the global market, it is necessary to integrate the knowledge and experience of all actives, correlate decisive process parameters, analyse a high amount of data, work with reliable information and have a prediction system that will facilitate critical decisions before incidences occur. It is essential to relate the most important variables, prioritise them and have a total control on the production parameters that will allow parts to be produced according to specifications.

The advanced prediction tool presented in this work solves two fundamental aspects from the foundry process:

- Knowledge management and integration of people's expertise into an intelligent system.
- Outcome prediction capacity. Previous actions can be performed in order to avoid incidences.

Experimental plan

The complexity of the foundry process forces us to spend important efforts in facing daily problem resolutions. The rational integration of knowledge along with the poor quality costs, the unknown origin of the defects and the need to reach rejection values in ppm levels require us to modify the actual way of solving problems and the knowledge management.

The leading and most competitive foundries in the market use on a daily basis strict process control systems along with design methods based in simulation tools. In some cases, the use of mechanical engineering systems and validation methods allow us to take an active role in co-engineering projects with the final customer.

The information given by the process is very valuable and it gathers a significant part of the own foundry knowledge. The key element might not be the lack of information from the process, but the ability to collect and analyse this data, since the conventional systems are not capable of managing and relate them in the most adequate and efficient way.

From a theoretical point of view, two working methodologies can be established for the incidence analysis and knowledge management: a conventional or a predictive system.

Conventional system. The main purpose is to maintain the different process parameters within the control limits. A huge amount of data is produced without any clear priority, and the different areas of the plant take care of their own self contained information with none or seldom inter connections to others. When a problem occurs, the identification of the real root cause is extremely difficult and in most cases, the final results are unfruitful, even after an important effort. Through these conventional systems it is very difficult to establish cause and effect relationships, since an important part of the available information is not relevant.

Predictive system. We are speaking about an objective working methodology with the capacity to perform multi variable analysis, to identify the most critical parameters and to integrate knowledge by a continuous learning. The combination of all these elements in a computer and the use of advanced mathematical algorithms, equals a real predictive system (fig.1).

The use of this tool allows operation in a proactive way, taking the necessary corrective measures before the problems appear. Data processing is performed in real time, which is one of the most important characteristics, and a helpful tool in order to take the appropriate decisions at the proper time.

Basic objectives. The development of this process control and knowledge management tool requires dealing with the following basic difficulties:

- Analytical capacity for a high volume of information.
- Possibility to establish inter-connections among the most relevant process parameters, prioritising each one of them.
- Global knowledge process control, incorporating all available means.
- Identify the actions that bring no improvement to the process.
- Integrate the experience and personnel knowledge existing in the company into an expert management system.

In the set-up and validation of this advanced tool the following stages of the analytical process have been identified:

- *Identification:* Selection of the defect or incidence to be analysed based on importance or scope criteria.
- *Analysis:* After gathering all the information available from the process the most relevant parameters are identified and analysed. It is important to count at this stage with all the plant available means.
- *Causal maps:* An initial network is developed including a clear identification of all the potential failure parameters (fig. 2).
- *Prediction:* Industrial production try outs are designed and carried out with a later analysis of results. Every analytical procedure gathers and records all the process information.
- *Network fine tuning:* From all variables initially considered, the system rejects all the ones that have no influence on the problem analysed.
- *Implementation:* The system will adapt to the different conditions of each fabrication and is able to manage the process in real time.
- *Feed back and learning:* The system updates automatically all the relevant information with a continuous improvement on the control and final response of the process.

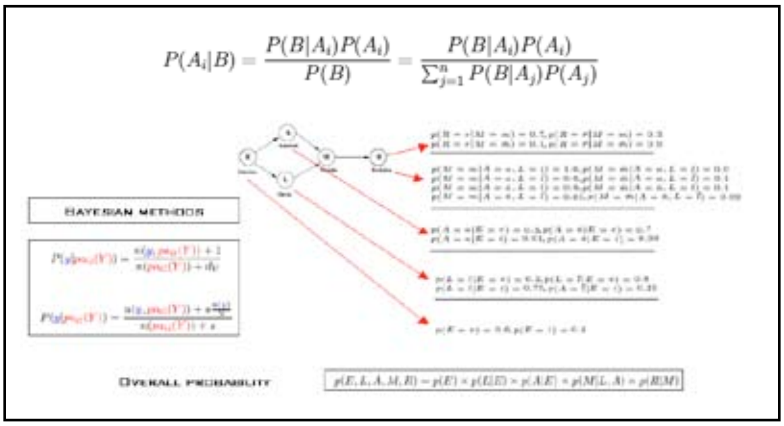

Fig. 1 Mathematical alogorithms corresponding to the Bayesian analysis

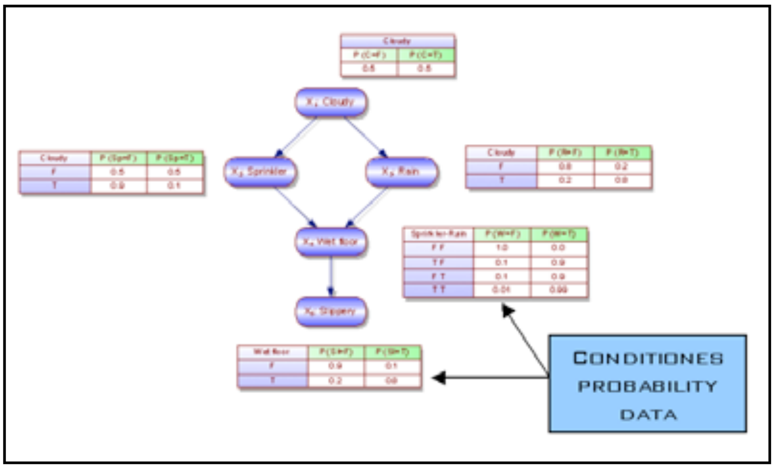

Fig. 2 Structure of a casual probability network

Having into consideration that this prediction tool is designed to manage all the information from the process, the validation procedure has been done in capable foundries with a high volume production of castings for the automotive industry:

- Solid industrial process with automatic moulding using a Disamatic.
- Important process controls and powerful data collection systems.
- Safety castings. Front bi-cylinder brake calipers are analysed (three different references).
- References are considered critical with an erratic behaviour. Almost all production batches have defective parts.
- Incidence considered as critical due to leaks in the hydraulic testing of the component. Internal micro shrinkage cavities produced by the secondary contraction of the metal.
- Inspection criteria. 100% of the parts are controlled by x-ray.

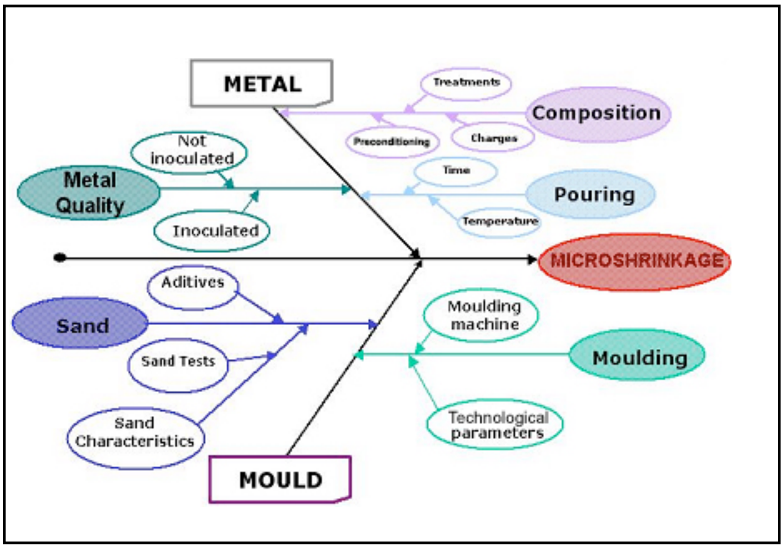

Fig. 3 Chart with the different process parameters to the probability network

- Average rejection rate of 2.7%.

One of the most difficult defects to control in the production of ductile iron castings is known as micro-shrinkage, since almost all process parameters interact on the secondary contraction of the metal. In addition, we must consider the critical status defined by the customer on hydraulic leakage problems of this brake component.

Fig.3 shows the different process parameters that have a direct influence in the development of secondary contraction. The study and subsequent control is done by the foundry technicians introducing their knowledge into the system. The fact of having a big number of variables does not mean any additional difficulty, since the system itself is able to refine and select the parameters that have a relevant influence. Possible intuitive, personal or subjective interpretations are left out. The analysis of data and real results from the experimental phase is performed by the system, so the primary number of chosen variables is reduced drastically.

Results

The experimental plan is focused exclusively on the irregularity or defect known as micro-shrinkage (fig.4). It is necessary to clarify that many variables of different nature are involved in the formation of this failure and their selection and correlation is always quite complex. The three references analysed show an inconsistent behaviour with production batches fully acceptable and other that have an alarming rejection rate (close to 5%).

This defect has a subcutaneous presence and therefore the evaluation must be done according to nondestructive X-ray and US testing techniques (fig. 5). The acceptance/rejection criteria is the one applied by the final requirements of the customer, in this particular case, established by the automotive industry. Any indication of defect, no matter the size, means a non acceptance and final rejection of the part. In the case that any doubt appears in the final interpretation, US inspection has also been performed.

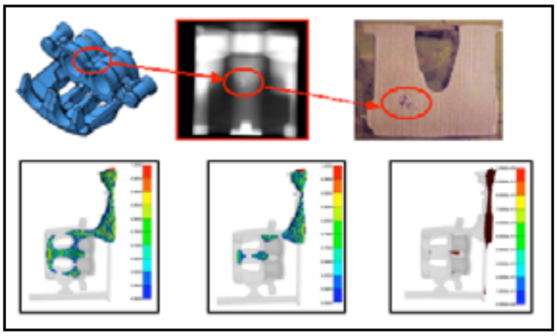

Fig. 4 The experimental plan is carried out to avoid micro-shrinkage in bi-cylinder callipers

Fig. 5 x-ray inspection is applied in the final control of the parts

As exposed previously, during the design of the experimental plan it has been necessary to identify potential root causes of the defect for a further analysis. Dimensional and geometry parameters also have an influence on this defect, including design conditions in the potential causes.

In all the different analytical cases, besides the inspection of all the parts of the mould, complete data from the 'potential risk factors' are recorded because the design of experiments will use all the identified variables. This analytical phase is essential since the complete experience and knowledge from the process is transferred to the system. The study of results allows the

Part identification	Analytical procedures	Rejection rate (average value)	Determining factors identified by the system	Remarks
A (FYTASA, S.A.)	427	4.2%	Quality of the mould Residual Mg Metallurgical quality	Critical design of the parts
B (FYTASA, S.A.)	388	2.7%	TE (min) and Recalescence Inoculation (quality of the inoculant)	Iron Metallurgy
C (FUCHOSA, S.L.)	289	1.3%	Shooting pressure Pouring temperature Recalescence	Metallurgical and technological parameters

Table 1. Summary of the experimental phase focused on the three references tested in industrial production.

implementation and evaluation of this knowledge (Table 1).

Design. The common criteria used in the design of cast components is related to the final function of the part. The corresponding validation analysis previous to industrialisation is orientated in this direction (prototypes, dynamic properties, test bench, etc). Production feasibility analysis is considered as a secondary feature, or even is not taken into consideration. It is usual to find incidences during the industrial production phase that could have been solved in the previous stage of design.

It seems obvious that the design of castings should be complemented by the knowledge of foundry technology, and therefore, the active participation of foundry technicians on design tasks is considered crucial.

The analysis related to the design of the moulding patterns, feeding and filling system has been done by PAM-QUIKCAST™, showing the three analysed references have a clear tendency to develop secondary contraction problems. Without any doubt, this tendency could have been reduced or even eliminated during the design stage, so the production process would have improved significantly.

In spite of this micro-shrinkage tendency, the final outcome is that most of the produced parts are free of this contraction defect and therefore the key is to design a process capable of reducing this deviation, although process variability is restricted significantly.

Metallurgical quality. The system has verified that the control on the chemical composition is not enough, since two melts with the same or similar chemical analysis behave totally differently in terms of secondary contraction.

The metallurgical control of the iron has been performed by thermal analysis (Thermolan). Production of parts with melts of different metallurgical quality has been carried out, although the chemical composition was among the specified limits for all of them.

Referred to the analysed defect of secondary contraction, the system has been able to identify the following metallurgical keys:

- Residual Mg. When increasing the level of residual magnesium there is a direct relationship on the appearance of the defect, and consequently in the number of rejected parts. Values higher than 0.042% have a critical behaviour.
- $T_{E(min)}$. A higher undercooling means as well an increase in the rejected parts. The $T_{E(min)}$ should not be lower than 1.345°C.
- Recalescence. Values higher than 3°C introduce an important risk in production.

When minimising the variability of the metallurgical quality of the iron, it has been necessary to modify the FeSiMg (FeSiMg 5% + La, instead of FeSiMg 8-10%) and the inoculation alloys (Zr inoculants are substituted by others that contain rare earths). Regarding the inoculants, it must be pointed out that a variation in the quantity of product applied has no effect in the results. It has been verified throughout the tests that a good iron pre-conditioning (0.25% of Desulco 9012S) allows a reduction in addition of inoculant down to 0.075%.

Characteristics of the mould. When analysing the characteristics of the mould it has been necessary to act upon the greensand and upon the moulding conditions and the parameters of the machine. Concepts such as mould stability have been taken into consideration all the time and so, extreme situations have also been analysed.

It has been observed that as the greensand strength is reduced, the number of faulty parts increases. At the same time, as the wet tensile strength is reduced, the defect becomes more severe.

All the machine parameters have been looked into - shooting and squeezing pressure being the most relevant ones.

Technological parameters. The influence of the pouring temperature and the filling time have been evaluated. In the first case, the extreme temperatures have a range between 1.375-1.425°C, whereas in the second one, the upper limit has always been settled within the machine time cycle.

The system has proved that the filling time exerts little effect while the pouring temperature is a factor that must be considered. The best thermal levels range between 1.380-1.390°C.

Filling and feeding systems. The study and validation of the filling and feeding processes is carried out by means of simulation tools. As far as the filling is concerned, two aspects have been tackled:

- Sequential filling. Influence of filling level by level.
- Ingates layout. The aim was to minimise the heating of critical areas.

The feeding system is designed in order to solve primary shrinkage problems, although some changes have been conducted in order to reduce the micro-shrinkage defect. The prediction system informs on the influence of the riser's size over micro-shrinkage, since when increasing the size of the riser the defect tends to be minimised.

After the optimisation and validation of the filling and feeding systems of the three references, no more changes are introduced since the system has discarded them for not being critical influence factors. According to the simulation studies it is not possible to explain the erratic behaviour of the process.

Discussions

The design tools and the control systems currently used in foundries work independently having no relationship between them. This situation is worse when it is necessary to give priority or discard one of them in accordance to their importance.

Artificial intelligence in general, and Bayesian networks specifically, can be successfully adapted to the foundry process control; thus, making the analysing of a huge number of data in real time possible (fig. 6).

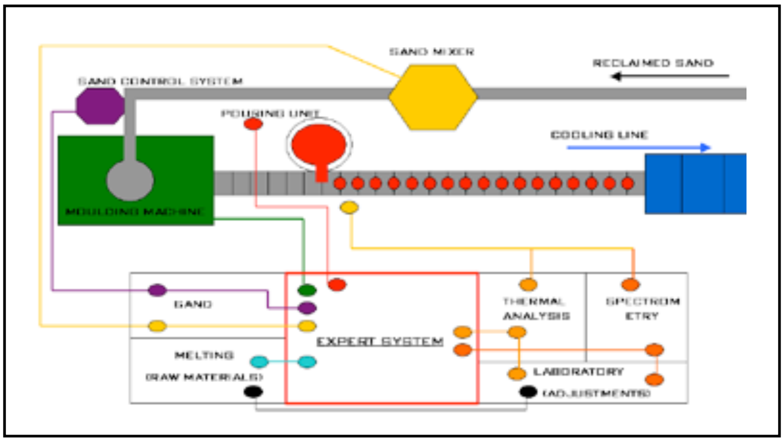

Fig. 6 Integration of the predictive system into the foundry process

The system analyses all the variables which have been initially identified as 'potential causes' of micro-shrinkage formation, and, out of them, it selects a limited number. The prediction tests and the expert supervision allows the initially built network to be improved progressively by eliminating all those variables that exert no influence on the defect.

The tool integrates all the significant variables, it analyses them in real time and finally, it gives all the necessary information in order to state the final feasibility of the production in question. According to that information, it is then decided whether it is convenient or not to carry out production.

In the specific case of micro-shrinkage, out of 47 variables initially identified and introduced into the expert system, the network has reduced them to nine. A data acquisition plan has been designed according to those nine variables. The results are analysed and the system itself, besides getting additional feedback, informs on the real state of the process.

Those productions identified by the system as 'no risk situations' are completely free of defects. On the contrary, in those productions where the prediction tool has diagnosed risk situations, a lot of faulty parts appear in different production orders. These results help to decide on the way to face the next stages of the production or to give an opinion on the severity of the inspection plans (Table 2).

Conclusions

A significant part of the success of the foundry industry is due to the rational use of the different prediction systems, only when they are fitted into the process. There is no doubt that technology is a good partner, but knowledge and its correct management are determining factors for success.

The causal probability networks, used as the mathematical basics for the development of this tool, allow it to inter-relate different events. The system can process a high volume of information by the use of advanced mathematical algorithms.

From the uncertainty connected with any casting production, as the analyses of the results are always conducted afterwards, this predictive tool allows decisions to be taken on whether it is convenient to carry on with a given production, since the system provides real time information on the risk level existing at that moment.

This prediction system gives the ability to integrate the already existing knowledge in the plant, as the use of this knowledge is basic for the characterisation of incidents and the identification of variables. Also, any other documental source whenever it has been conveniently contrasted, can be integrated in the system as well.

In any technological process, and especially in a foundry, the most competitive differences are based on knowledge and technology. This tool helps to integrate people's knowledge into the productive process, thus remaining as the background of that specific situation.

Part identification	Prediction	Success level
A	Risk situation No risk situation	87% 96%
B	Risk situation No risk situation	92% 100%
C	Risk situation No risk situation	95% 100%

Table 2. Success level on the different predictions.

The future development of this predictive tool is oriented towards the widening of the system's capacity, the automation of the data acquisition, the integration of knowledge within a global network of incident analysis and the incorporation of the structure prediction of the material.

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