Efficient failure-free Foundry Production

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Abstract

Microshrinkages are known as probably the most difficult defects to avoid in high-precision foundry. Depending on the magnitude of this defect, the piece in which it appears must be rejected with the subsequent cost increment. Modelling this environment as a probabilistic constellation of interrelated variables allows Bayesian networks to infer causal relationships. In other words, they may guess the value of a variable (for instance, the presence or not of a defect). Against this background, we present here the first microshrinkage prediction system that, upon the basis of a Bayesian network, is able to foresee the apparition of this defect and to determine whether the piece is still acceptable or not. Further, after testing this system in a real foundry, we discuss the obtained results and present a risk-level-based production methodology that increases the rate of valid manufactured pieces.

1. Introduction

The ancient magic-surrounded metal castings techniques have evolved into a key activity that maintains the world as we know it today. Foundry supplies many other industries with components they need to carry on their respective mission. Naval, aeronautic, weapon or automotive industry, for instance, require special pieces that, in many cases, play determining roles as for instance brakes, wind castings or aeroplane components. In these situations, the tiniest defect may become fatal.

Currently, safety measures to assure this failure-free manufacturing includes exhaustive production control and diverse simulation techniques but they are extremely expensive and only achieve good results in an a posteriori fashion.

Unfortunately, they are still not able to prevent what is known to be the most difficult flaw in ductile iron castings, namely the microshrinkage. This imperfection, also known as secondary contraction, consists of tiny porosities that appear when the casting is cooling down, and almost all process parameters interact on its apparition making it impossible to avoid so far. The biggest problem associated to microshrinkages is that pieces flawed with this defect must be discarded. Moreover, triggered either by an increment on the amount of disposed castings in the routine quality inspections (with random-picked pieces), or after a client’s reclamation, security measures stipulate that all castings of that production series must be ultrasound-scanned in order to discover new possible faulty pieces. This procedure entails the subsequent cost increment, which has to be added to the cost of the discarded castings themselves (transport, energy to melt again, new production process and still no guaranty that this time is going to work).

Further, the problem of the microshrinkage apparition is very difficult to solve due to the following reasons. First, many variables take part in the creation of the secondary contraction. Second, the data-acquisition systems gather much information but it is not prioritised or categorised in any way. Third, it is very difficult to establish cause-effect relationships between the variables of the system. And, last but not least, human problem-knowledge used in this task tends to be subjective, incomplete and not subjected to any empirical test. Therefore, predicting the presence of microshrinkage demands overcoming all these obstacles.

In a previous work we presented a microshrinkage prediction system based on a Bayesian network. These probabilistic nodes are very helpful when facing problems that require predicting the outcome of a system consisting of a high number of interrelated variables. After a training period, the Bayesian network learns the behaviour of the model and, thereafter it is able to foresee its outcome. In this way, the production process of a foundry is perfectly suitable to be modelled as system of variables whose behaviour may induce the apparition of microshrinkages.

Still, sometimes microshrinkages are too small or appear in a non-important position so the piece does not need to be discarded. Against this background, this paper advances the state of the art in 2 main ways. First, we present, for the first time, a new generation of the Bayesian network prediction system that is sensitive enough to distinguish between valid and invalid microshrinkages. Second, we introduce a risk-level-based production methodology that helps finding a trade-off among usage of production capacity and acceptable faulty castings rate.

The remainder of the paper is organised as follows. Section 2 details the casting production process in an iron foundry. Section 3 examines the problem we deal with
Cost. Moreover, the application of such measures entirely matters to the direct rejection of it without any other control, in this case, ranging from the exhaustive control of the moulds taken.

Not acceptable, a decision on what to do with the rest of the production is found, then the failure procedure starts. The first step is the assessment of the damage: depending on the number of the pieces involved, the position of the defect, its size and so on, a microshrinkage can be acceptable (i.e., the flaw is minor) and, therefore, the piece must not be discarded. On the contrary, if the microshrinkage is not acceptable, a decision on what to do with the rest of the lot must be taken.

There are a number of measures that can be applied in this case, ranging from the exhaustive control of the lot to the direct rejection of it without any other control, and each of them has different consequences in terms of cost. Moreover, the application of such measures entirely depend on the person in charge of the production.

In any case, one of the biggest problems to face is that the decision is taken when the lot has been already produced. This is, according to current data-acquisition techniques, the process to analyse control moulds may take up to one hour in which production does not stop. Hundreds of moulds (i.e., thousand of pieces) may be manufactured before any decision is reached. Moreover, the mere act of controlling some pieces demands an effort and extra cost that does not add any value to the product (and that is not reflected on its price). In this way, we need prediction tools that replace quality controls so correction measures may be adopted when necessary.

The Bayesian network presented in a previous publication [2], having learned the working way of a certain foundry, is able to foresee the apparition of microshrinkages. Here, it has been further trained to distinguish between valid and invalid microshrinkages. In this way, we expect it to remove uncertainty from the foundry process and, since the number of rejected pieces decreases, so does the cost associated to this problem.

4 Experiments and results

We have applied the described tool and methodology to a foundry (Fuchosa S.L. standing in Atxondo, Biscay, Basque Country) of safety and precision components in nodular cast iron mainly for the automotive industry; it is specialised in braking system components (principally in disk-brake support) with a production over 45,000 tons a year.

The experimental plan is focused exclusively in the micro-shrinkage. Note that, as already mentioned, microshrinkages have subcutaneous presence and therefore the evaluation must be done according to non-destructive X-ray, first, and ultrasound testing techniques thereafter to ensure that even the smallest microshrinkages are found [4]. The acceptance/rejection criterion of the Bayesian network resembles the one applied by the final requirements of the customer (this is, in the examined cases, the automotive industry). According to the very restrictive quality standards imposed by these clients, pieces flawed with an invalid microshrinkage must be rejected.

The Bayesian network was fed with real data of the foundry and the training consisted on the simulation of manufacturing situations whose output had been registered in beforehand. After the Bayesian network was tuned up properly, it was applied to predict the outcome of 174 normal production lots that were also double-checked by ultrasound techniques afterwards. In this way, it detected 27 invalid microshrinkages (the 15.5%) and in 147 cases (the 84.5%) the piece was valid or contained a valid microshrinkage.

The criteria that help distinguish valid from invalid microshrinkage are agreed with the client on beforehand. Moreover, when the Bayesian network foresees the possible apparition of a microshrinkage (valid or invalid), the defect can be avoided by stopping the casting of that piece and starting the production of another one (usually with a lower sensibility) [4].

For the same 174 production lots examined by ultrasound, the Bayesian network predicted risk of microshrinkage in 66 cases and 23 of them showed it indeed (34.5%). In 98 of the cases it foresaw a safe production, showing an error rate of the 3.1% (3 castings out of the 98
marked as safe). This is, the Bayesian network predicted the absence of the defect in the 56% of cases and, according to the ultrasound controls performed afterwards to test the skill of the prediction system, only the 3.1% of those presented it. Moreover, it detected that microshrinkages could appear in the 37.93% of the cases and this actually happened in the 34% of them (which was the 98.9% of the total microshrinkages). Thus, taking into account that only failure-free pieces or those with valid microshrinkages can be sold and the rest must be melt and re-cast, the productivity rises by 11.4% when the Bayesian network is used as prediction system.

Moreover, only the 85% of the pieces manufactured without prediction system were valid whereas the Bayesian network helps push this amount up to the 96.9%. In this way, the need of completely or partially inspect production batches was similarly reduced in an 80% since without the prediction system, quality controls must be applied whenever faulty lots appear (i.e. the 15.5%). With the help of the Bayesian network, such measures were only needed in case the system predicts the presence of microshrinkage (i.e. the 3.1%), and only if the production was not stopped as the negative verdict is issued. Subsequent costs such as time to re-cast flawed pieces, personnel involved, energy and so on, decrease in the same proportion.

Nevertheless, 98 safe situations detected out of 174 is still too less since the rest 66, marked as risky, included some which did not present the defect or it was acceptable. Therefore, we have designed a second experiment in which we define risk levels to increase the accuracy of the predictions. These risk levels model the sensitivity of the system and, in this way, help better classify the outcome of each production situation (i.e. whether a microshrinkage will appear and whether it will be valid or invalid). Please note that such levels are established in an experimental manner and, therefore, are subject to change according to the specific features and conditions of each foundry.

The definition of these risk levels is achieved as follows: the Bayesian network uses the analysis on the first lot (i.e. 3 consecutive moulds, 8 pieces each) of the production series to infer the behaviour of the rest. According to this result, the risk of every lot is classified into Risk 0 (no microshrinkages foreseen), Risk 1 (less than 5 valid microshrinkages expected), Risk 2 (more than 5 valid microshrinkages predicted), and Risk 3 (invalid microshrinkages foreseen).

The verdict of the prediction system arrives to the person in charge, and she decides whether to carry on with the production or not (this procedure can be also automated by selecting a maximum accepted risk level). In order to test the performance of this new feature of the Bayesian network, we have applied it to a whole production of 307 lots (i.e. 7368 pieces altogether), which was also controlled by ultrasound afterwards to compare the results, shown in Table 1.

As it can be seen, only working under risk 0 assures a completely failure-free production, and this level was predicted in a 32.89% of the cases (101 out of 307). Moreover, 99 lots (32.28%) where labelled as risk 1 (i.e. less than 5 valid microshrinkages expected), in which the ultrasound exam revealed 8 cases (8.08%, 2.6% of the total) with more than 5 valid microshrinkages and 3 cases that had to be rejected due to invalid microshrinkages (3.03%, 0.97% of the total). Therefore, risk 1 predictions presented an 11.11% error rate (lots with more than 5 valid microshrinkages plus lots with invalid ones), though those with more than 5 valid microshrinkages are still acceptable. Similarly, the error rate of risk 2 was 5.66% (3 cases with invalid defect out of 53) and, in risk 3 situations, since the possibility of invalid microshrinkages was foreseen, there was no error in the prediction but the 29.62% of the lots contained faulty pieces.

If we also consider these results together with how would it be to produce without prediction system, we obtain Fig.1, which compares the behaviour of several lots with different risk levels in terms of the amount of (valid/invalid) microshrinkages.

![Figure 1. Microshrinkage presence and type depending on risk levels](image)

Therefore, manufacturing castings under risk 0 implies no possibility at all of faulty pieces whereas risk 3 is more likely to produce them even that without prediction system.

Finally, there is another aspect worth to be analysed: the relationship between the safety level (say acceptable risk) and the amount of pieces produced per hour. If the safety policy of the foundry is, for instance, risk 0, only castings whose risk prediction equals 0 will be manufactured. In case it is risk 1, lots with risk 1 and risk 0 will, and so on. In this way, Fig. 2 illustrates how does the amount of faulty castings relate to the production capacity according to the selected safety level.

In this way, according to an a priori test of each casting, the foundry must choose between an slower but safer production speed and a faster one eventually containing faulty pieces. According to these results, one could say that using the Bayesian network slows the production speed or, at least, that it reduces the flexibility of the manufacturing process. In other words, the choice to cast one piece or another, according to the demand and plant sched-
Table 1. Results of applying risk-level-based detection.

<table>
<thead>
<tr>
<th>Risk level</th>
<th>No microshrinkages</th>
<th>&lt;5 valid microshrinkages</th>
<th>&gt;5 valid microshrinkages</th>
<th>Invalid microshrinkage(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk 0</td>
<td>86/101 (85.14%)</td>
<td>11/101 (10.89%)</td>
<td>4/101 (3.96%)</td>
<td>0/101 (0%)</td>
</tr>
<tr>
<td>Risk 1</td>
<td>73/99 (73.73%)</td>
<td>15/99 (15.15%)</td>
<td>8/99 (8.08%)</td>
<td>3/99 (3.03%)</td>
</tr>
<tr>
<td>Risk 2</td>
<td>32/53 (60.37%)</td>
<td>10/53 (18.86%)</td>
<td>8/53 (15.09%)</td>
<td>3/53 (5.66%)</td>
</tr>
<tr>
<td>Risk 3</td>
<td>13/54 (24.07%)</td>
<td>16/54 (29.62%)</td>
<td>15/99 (15.15%)</td>
<td>16/54 (29.62%)</td>
</tr>
<tr>
<td>Total lots with this risk level</td>
<td>101/307 (32.89%)</td>
<td>99/307 (32.47%)</td>
<td>55/307 (17.91%)</td>
<td>54/307 (17.58%)</td>
</tr>
</tbody>
</table>

Figure 2. Relationship among productivity, risk level and amount of faulty castings.

In order to tackle this point, we should take several aspects into consideration. First, productivity cannot be evaluated only in terms of amount of pieces manufactured per hour. Costs derived from quality controls and re-castings should be also taken into account. Second, regarding the lack of flexibility, the prediction system does not recommend stopping the whole production, but stopping the production of a certain casting. Each one has a different sensibility and, as already stated, when the Bayesian network predicts a risk level above the maximum accepted one, the manufacturing of that casting may be momentarily replaced by a less risky one.

5 Conclusion

Predicting the apparition of microshrinkages in ductile iron castings is one of the most difficult challenges in foundry-related research. In this paper, we present the application of a Bayesian network as the tool that allows to foresee the presence of microshrinkages. This prediction system enables the integration of the already existing knowledge in the plant, since the use of this knowledge is basic for the characterization of incidents and the identification of variables. As presented in a previous work, to our knowledge there is no related work so far applying Artificial Intelligence techniques to the prediction of microshrinkages. In this paper, we present a Bayesian network that is able to foresee the presence of such defect and distinguish whether it will be acceptable or not.

We have tested this system in a real situation and results show that avoiding the production of castings expected to be faulty increases the amount of manufactured failure-free pieces by 11.4%. Moreover, the need of an a posteriori ultrasound quality inspections is reduced by 80%, with the consequent reduction in costs associated to quality controls and so on. Finally, we have also presented a production methodology based on risk levels. Here, the Bayesian network issues a verdict assessing the possibility that a certain lot is failure-free, presents less than 5 valid microshrinkages, more than 5 valid microshrinkages or any invalid microshrinkage. We have tested this policy evaluating the consequences of producing beneath a certain risk threshold. For instance, if risk 1 is selected, only lots labelled with risk 1 and risk 0 will be produced. The results illustrate the relationship between the production speed of valid castings and the possibility of having invalid ones (i.e. with the subsequent quality-check costs), according to each risk level. Such methodology helps the foundry find a trade-off between these characteristics according to their demand requirements and capacities.

The future development of this predictive tool is oriented in three main directions. First, we plan to extend our analysis to the prediction of other defects (such as inclusions and carbides) in order to develop a global network of incident analysis. Second, we will focus on designing a fully-automated data acquisition in spite of the hard environmental conditions (for instance, wireless sensors sometimes get inhibited). Finally, further extension of the system, with for instance structure prediction of the material demands a more detailed study.

References