Optimising Machine-Learning-Based Fault Prediction in Foundry Production

Igor Santos, Javier Nieves, Yoseba K. Penya, and Pablo G. Bringas

Deusto Technology Foundation
University of Deusto
Bilbao, Basque Country
{isantos,jnieves,ypenya,pgb}@tecnologico.deusto.es

Abstract. Microshrinkages are known as probably the most difficult defects to avoid in high-precision foundry. The presence of this failure renders the casting invalid, with the subsequent cost increment. Modelling the foundry process as an expert knowledge cloud allows properly-trained machine learning algorithms to foresee the value of a certain variable, in this case the probability that a microshrinkage appears within a casting. Extending previous research that presented outstanding results with a Bayesian-network-based approach, we have adapted and tested an artificial neural network and the K-nearest neighbour algorithm for the same objective. Finally, we compare the obtained results and show that Bayesian networks are more suitable than the rest of the counterparts for the prediction of microshrinkages.

Keywords: Machine learning, data mining, fault prediction.

1 Introduction

Despite of being one of the axis of the world as we know it, foundry is still at a development level lower than that of industries of similar importance. More specifically, since foundry supplies for instance naval, aeronautic, weapon or automotive industries with key pieces, the foundry process is subject to a very strict safety controls in order to ensure the quality of the products. Yet, the exhaustive production control and diverse simulation techniques [1] performed are extremely expensive and usually entail the destruction of the piece examined.

As shown in [2], computer science can help in this goal. For instance, when preventing what is known to be the most difficult flaw in ductile iron castings, namely the microshrinkage. This imperfection, also called 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 [3].The biggest problem associated to pieces with microshrinkages is that they must be rejected since it becomes more fragile..

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

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series must be X-ray or 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 have an effect 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 hard to establish cause-effect relationships between the variables of the system. Finally, human problem knowledge used in this task inclines to be subjective, incomplete and not subjected to any empirical test [3]. Hence, predicting the apparition of microshrinkage demands surpassing all these obstacles.

In a previous work ,we presented a microshrinkage prediction system based on a Bayesian network. After a training period, the Bayesian network learned the behaviour of the model and, thereafter it was able to foresee its outcome [2] (i.e. the formation or not of the microshrinkage). Further, we presented a risk-level-based production methodology that helped finding a trade-off among exploiting the full production capacity and acceptable faulty castings rate [4].

Still, there are several supervised machine learning algorithms that have been applied in similar problem domains with remarkable results, principally artificial neural networks [5] or the K-nearest neighbour algorithm [6]. In this way, successful applications of artificial neural networks include for instance spam filtering [7], intrusion detection [8] or industrial fault diagnosis [9]. Similarly, K-nearest neighbour algorithm is applied for instance in visual category recognition [10], automated transporter prediction [11] or image retrieval [12].

Against this background, this paper advances the state of the art in two main ways. First, we describe a methodology to adapt machine learning classifiers to the foundry production system and the way to train them. Second, we evaluate them with data obtained from a real foundry process in order to compare the accuracy and suitability of each method.

The remainder of the paper is organised as follows. Section 2 presents and analyses related work. Section 3 details the casting production process in an iron foundry. Section 4 describes the experiments performed and section 5 examines the obtained results and explains feasible enhancements. Finally, section 6 concludes and outlines the avenues of future work.

2 Related Work

There has been a hectic activity around the applications of neural networks to several other problems of foundry process, for instance on the prediction of the ferrite number in stainless steel arc welds [13]. Similarly, successful experiments involving K-nearest neighbour algorithm include fault detection of semiconductor manufacturing processes [14].

In a verge closer to our view, neural networks have been used for optimising casting parameters [15]. More accurately, they simulate a casting process with predicted values of the parameters; the simulation results and the predicted ones were nearly the same (a difference of 4mm). In addition, K-nearest neighbour algorithm and artificial neural networks have been applied for enhance quality of steel [16] that achieves an overall root mean square error of 0.38. The excellent results obtained for these works have encouraged us to tailor these approaches into our concrete problem domain.

3 Casting Production in Foundry Processes

The foundry processes are known to be very complex starting from the extreme conditions they are carried out. Microshrinkages appear during the cooling phase of the metal but they cannot be noticed until the production is accomplished. More accurately, this flaw consists of minuscule internal porosities or cavities. Since metals are less dense as a liquid than as a solid, the density of the metal increases while it solidifies and the volume decreases in parallel. In this process, diminutive, microscopically undetectable interdendritic voids may appear leading to a reduction of the castings hardness and, in the cases faced here (where the casting is a part of a very sensitive piece), rendering the piece useless [17].

Unfortunately, the only way to examine finished parts is the usage of non-destructive inspections. In this way, the most common techniques are X-ray and ultrasound emissions but both require suitable devices, specialised staff and quite a long time to analyse all the produced parts. Therefore, post-production inspection is not an economical alternative to the pre-production detection of microshrinkages.

As aforementioned, the complexity of detecting secondary contractions arises principally from the high number of variables that participate in production process and, therefore, may have influence on the final design of a casting.

In this way, the main variables to control in order to predict the apparition of microshrinkages are:

- **Metal-related:**
  - *Composition:* Type of treatment, inoculation and charges.
  - *Nucleation potential and melt quality:* Obtained by means of a thermal analysis program [18].
  - *Pouring:* Duration of the pouring process and temperature.
- **Mould-related:**
  - *Sand:* Type of additives used, sand-specific features and carrying out of previous test or not.
  - *Moulding:* Machine used and moulding parameters

Commonly, the dimension and geometry of the casting play a very important role in this practice and, thus, we also include several variables to control this two features. In the same way, the system should take into account parameters related to the configuration of each machine that works in the manufacturing process [19].

Furthermore, there are some variables that may influence the apparition of second contraction during the foundry process, such as the composition [20], the size of the casting, the cooling speed and thermal treatment [21] [22]. The system must take into account all of them in order to issue a prediction on those mechanical properties. In this way, the machine-learning classifiers used in our experiments are composed of about 24 variables.

4 Experiments and Results

We have collected data from a foundry specialised in safety and precision components for the automotive industry, principally in disk-brake support with a production over 45000 tons a year.

The experiments are focused exclusively in the microshrinkage prediction. Note that, as aforementioned, microshrinkages have subcutaneous presence, thus the evaluation must be done according to non-destructive X-ray, first, and ultrasound testing techniques thenceforth to ensure that even the smallest microshrinkages are found [3].

Moreover, the acceptance/rejection criterion of the studied models resembles the one applied by the final requirements of the customer (i.e, 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.

To this extent, following the methodology developed in [4], we have defined risk levels as follows: Risk 0 (no microshrinkages foreseen), Risk 1 (low microshrinkage risk foreseen), Risk 2 (high microshrinkage risk foreseen), and Risk 3 (extreme microshrinkage risk foreseen).

In these experiments, the machine-learning classifiers has been built with the aforementioned 24 variables. We have worked with two different references (i.e. type of pieces) and, in order to test the accuracy of the predictions, with the results of the non-destructive X-ray and ultrasound inspections from 951 castings (note that each reference may involve several castings or pieces) performed in beforehand.

Using the aforementioned dataset, we followed the next methodology in order to properly evaluate the machine learning models we used:

- **Cross validation:** Despite the small dataset, we have to use as much of the available information in order to obtain a proper representation of the data. To this extent, *K-fold cross validation* is usually used in machine learning experiments [23]. In our experiments, we have performed a K-fold cross validation with $k = 10$. In this way, our dataset is 10 times split into 10 different sets of learning (66 % of the total dataset) and testing (34 % of the total data).
- **Learning the model:** For each fold, we have performed the learning phase of each algorithm with the corresponding training dataset, applying different parameters or learning algorithms depending on the model. More accurately, we have use the following models:

  - *Bayesian networks:* For Bayesian networks we have used different structural learning algorithms; K2 [24], Hill Climber [25] and Tree Augmented Naïve (TAN) [26]. Moreover, we have also performed experiments with a Naïve Bayes Classifier.
  - *K-nearest neighbour:* For *K-nearest neighbour* we have performed experiments with $k = 1$, $k = 2$, $k = 3$, $k = 4$, and $k = 5$.
  - *Artificial neural networks:* We have used a three-layer Multilayer Perceptron (MLP) learned with *backpropagation* algorithm. There are 24 X 3 units in the input layer, 15 units in the hidden layer, and 4 units in the output layer.
- **Testing the model:** For each fold, we evaluated the error rate between the predicted value set X and the real value set Y (both with the size of the testing dataset m) with mean absolute error (MAE) (shown in equation 1).

$$MAE(X,Y) = \sum_{i=1}^{m} \frac{|X_i - Y_i|}{m} \tag{1}$$

Similarly, we have used root mean square error (RMSE) (shown in equation 2)

$$RMSE(X,Y) = \frac{1}{m} \cdot \sqrt{\sum_{i=1}^{m} (X_i - Y_i)^2} \tag{2}$$

5 Results

Fig. 1 shows the obtained results in terms of prediction accuracy and fig. 2 shows the error rate of the three classifiers (mean absolute error and root mean square error). In this way, nearly every algorithm achieves good results, however both artificial neural networks and Bayesian networks trained with Tree Augmented

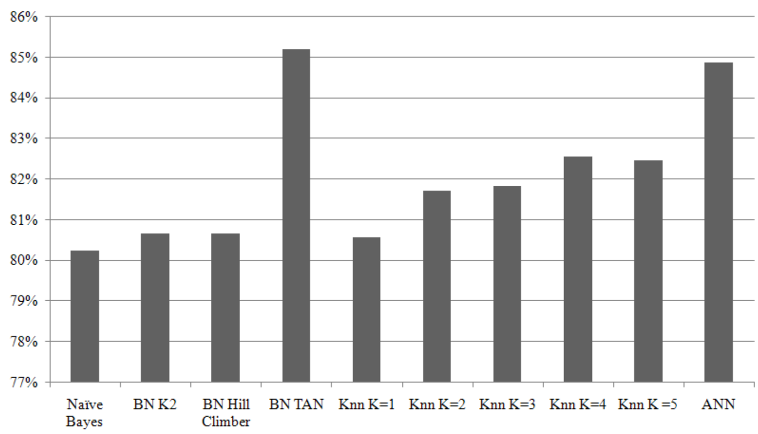

Fig. 1. Accuracy of Evaluated Classifiers

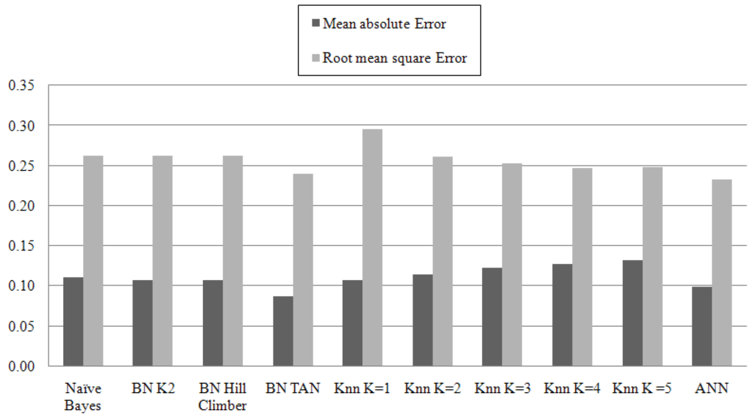

Fig. 2. Error Rate of Evaluated Classifiers

Naïve seem more suitable if we focus in the results. Still, Naïve Bayes classifier behaves worse than other classifiers. Please note that Naïve Bayes is a type of Bayesian network where the input variables are assumed to be linear independent. In this way, it skips the causal dependency that may be within the variables, therefore it cannot achieve as good results as the other classifiers.

Moreover, K-nearest neighbour algorithm, witch is a non-linear classifier, achieves better results than one may think in beforehand. In this way, K-nearest neighbour has no training phase itself (only a little data preprocessing), it only focuses in the resemblance between the instances. Therefore, it behaves worse than more robust methods such as ANN and Bayesian networks.

Actually, even the classifiers have not reached a 100% accuracy level, they have interesting results for being used in a high-precision foundry. Remarkably, the good results achieved by the ANN show that it can be used in a similar way as we have used the Bayesian networks in previous works. In this way, combining the better classifiers and using them for the defects that suit better, we can reduce in a significative manner the cost and the duration of the actual testing methods, apart from providing an effective *ex-ante* method.

6 Conclusions and Future Work

Predicting the apparition of microshrinkages in ductile iron castings is one of the most hard challenges in foundry-related research. Our work in [2] pioneers the application of Artificial Intelligence to the prediction of microshrinkages. This time, we focus on the methods used for the prediction of the microshrinkage. More accurately, we have adapted and evaluated three well-known machine learning classifiers with a long tradition in similar problem domains.

In this way, we have compared the results of their experiments with real foundry data in terms of prediction accuracy and error rate, showing that

Bayesian networks and artificial neural networks perform better than lazy methods as K-nearest neighbour.

Hence, Bayesian networks and artificial neural networks seem to be the best option to foresee microshrinkages, yet the K-nearest neighbour algorithm did not perform as bad as one could think on beforehand. Furthermore, taking into account the high computational cost of building an artificial neural network is very high, we conclude that Bayesian networks trained with Tree Augmented Naïve offers the best trade-off.

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 in order to develop a global network of incident analysis. Second, we will compare more supervised and semi-supervised machine learning algorithms in order to prove their effectiveness to predict foundry defects. Finally, we plan to integrate the best classifiers in meta-classifier combining the partial results.

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