Enhanced Foundry Production Control

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Abstract. Mechanical properties are the attributes that measure the faculty of a metal to withstand several loads and tensions. Specifically, *ultimate tensile strength* is the force a material can resist until it breaks and, thus, it is one of the variables to control in the foundry process. The only way to examine this feature is the use of destructive inspections that renders the casting invalid with the subsequent cost increment. Nevertheless, the foundry process can be modelled as an expert knowledge cloud upon which we may apply several machine learnings techniques that allow foreseeing the probability for a certain value of a variable to happen. In this paper, we extend previous research on foundry production control by adapting and testing support vector machines and decision trees for the prediction in beforehand of the mechanical properties of castings. Finally, we compare the obtained results and show that *decision trees* are more suitable than the rest of the counterparts for the prediction of ultimate tensile strength.

Keywords: fault prediction, machine-learning, industrial processes optimization.

1 Introduction

Foundry is one of the axis of current economy: thousands of castings are created in foundries around the world to be part of more complex systems, say for instance, brake of a car, propeller of a boat, wing of an aircraft or the trigger in a weapon. As one may think, the tiniest error may have fatal consequences and, therefore, if one of the pieces is found faulty, this fact can be detrimental to both individuals and for businesses activities.

Moreover, current trends encourage the production of smaller and more accurate components. It is really easy to produce castings and suddenly discover that every single one is faulty. Unfortunately, although there are many standards and methods to check the obtained parts, these are carried out once the production has been completed. In this way, the most used techniques for the assurance of failure-free foundry processes, are exhaustive production control and diverse simulation techniques [1] but they are extremely expensive and only achieve good

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results in an *a posteriori* fashion. Hence, providing effective *ex-ante* methods can help to increase the quality standards and to save resources in the process (i.e. saving money).

In this paper, we focus on the so-called *ultimate tensile strength* that is the force which a casting can withstand until it breaks, or in other words, it is the maximum stress any material can withstand when subjected to tension. Therefore, manufactured iron castings have to reach a certain value (threshold) of ultimate tensile strength in order to pass the strict quality tests.

As shown in [2,3], a machine-learning-based tool could help avoid these problems. In both approaches we presented a prediction system based on Bayesian networks. After a training period, the Bayesian network learnt the behaviour of the model and, thereafter, it was able to foresee its outcome illustrating how computer science can improve foundry production techniques.

Still, similar *machine-learning* classifiers have been applied in domains alike with outstanding results, for instance, neural networks [4] or the K-nearest neighbour algorithm [5]. In this way, successful applications of artificial neural networks include for instance spam filtering [6] or industrial fault diagnosis [7]. Similarly, K-nearest neighbour algorithm, despite its simplicity, has been applied for instance to automated transporter prediction [8] or malware detection [9]. These good results boosted us to test other machine learning models. Carrying out these experiments [10,11], we discovered that for each defect or property, the most accurate classifier was not always the same and, therefore, we decided to find out which classifier suited better to each domain.

Finally, some other machine learning models (as support vector machines [12] and decision trees [13]) have been used in less similar domains, such as, identification of gas turbine faults [14], fault diagnosis [15] and prediction [16].

Against this background, this paper advances the state of the art in two main ways. First, we address here a methodology to adapt machine learning classifiers, specifically support vector machines and decision trees, to the prediction of ultimate tensile strength and we describe the method for training them. Second, we evaluate the classifiers with an historical dataset from a real foundry process in order to compare the accuracy and suitability of each method.

The remainder of this paper is organised as follows. Section 2 details mechanical properties of iron castings, focusing on the ultimate tensile strength and how the foundry processes can affect them. Section 3 describes the experiments performed and section 4 examines the obtained results and explains feasible enhancements. Finally, section 5 concludes and outlines the avenues of future work.

2 Foundry Processes and Mechanical Properties

Several factors, for instance the extreme conditions in which it is carried out, contribute to render the foundry process very complex. Thereby, starting from the raw material to the final piece, this process has to go through numerous phases, some of which may be performed in parallel way. More accurately, when it refers to iron ductile castings, a simplification of this process presents the following phases.

First, the *melting and pouring phase* in which the raw metals are melt, mixed and poured onto the sand shapes . Second, the *moulding phase* in which the moulding machine forms and prepares the sand moulds. And last but not the least, the *cooling phase* where the solidification of the castings is controlled in the cooling lines until this process is finished.

When these aforementioned phases are accomplished, foundry materials are subject to forces (loads). Engineers calculate these forces and how the material deforms or breaks as a function of applied load, time or other conditions. Therefore, it is important to recognise how mechanical properties influence iron castings [17]. Specifically, the most important mechanical properties of foundry materials[18] such us strength (there are many kinds of strength as the ultimate tensile strength), hardness, resilience and elasticity.

Furthermore, there are common or standard procedures (i.e. ASTM standards [19]) for testing the value of mechanical properties of the materials in a laboratory. Unfortunately, in order to learn about these properties, scientists have to employ destructive inspections as the only possible method. Moreover, the process requires suitable devices, specialised staff and quite a long time to analyse the materials.

Regarding the ultimate tensile strength, on which we focus here on, its checking method is performed as follows. First, a scientist prepares a testing specimen from the original casting (see (1) in Figure 1). Second, the specimen is placed on the tensile testing machine (2). And finally, it pulls the sample from both ends and measures the force required to pull the specimen apart and how much the sample stretches before breaking.

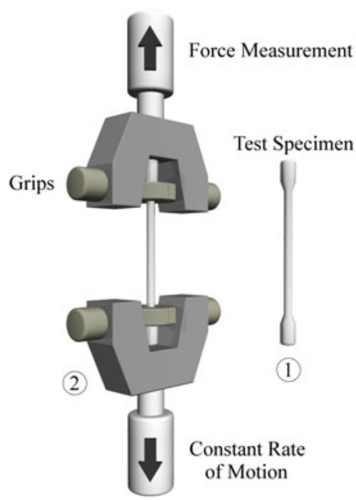

Fig. 1. Ultimate Tensile Strength Test

Moreover, the main variables to control in order to predict the mechanical properties of metals are the composition [20], the size of the casting, the cooling speed and thermal treatment [17,21]. In this way, the system should take into account all these variables in order to issue a prediction on those mechanical properties. Hence, the machine-learning models used in our experiments are composed of about 25 variables.

3 Experiments

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. These experiments are focused exclusively in the ultimate tensile strength prediction.

Moreover, the acceptance/rejection criterion of the studied models resembles the one applied by the final requirements of the customer. Pieces flawed with an invalid ultimate tensile strength must be rejected due to the very restrictive quality standards (which is an imposed practice by the automotive industry). To this extent, we have defined two risk levels: Risk 0 (more than 370 MPa) and Risk 1 (less than 370 MPa).

In these experiments, the machine-learning models have been built with the aforementioned 25 variables. We have worked with 11 different references (i.e. type of pieces) and, in order to test the accuracy of the predictions we have used as input data the results of the destructive inspection from 889 castings (note that each reference may involve several castings or pieces) performed in beforehand.

Specifically, we have conducted the next methodology in order to evaluate properly the machine-learning classifiers:

- **Cross validation:** We have performed a *k-fold cross validation* [22] with $k = 10$. In this way, our dataset is 10 times split into 10 different sets of learning.
- **Learning the model:** We have made the learning phase of each algorithm with each training dataset, applying different parameters or learning algorithms depending on the model. More accurately, we have use this three different models:
  - *Support Vector Machines:* In order to train Support Vector Machines we have used different kernels: a polynomial kernel, a normalised polynomial kernel, a Pearson VII function-based universal kernel and a radial basis function (RBF) based kernel.
  - *Decision Trees:* We have performed experiments with *random forest*, an ensemble of randomly constructed decision trees using different amount of trees (n): $n = 10$, $n = 50$, $n = 100$, $n = 150$, $n = 200$, $n = 250$ and $n = 300$. And we have also used *J48*.
  - *Artificial neural networks:* We have used a three-layer Multilayer Perceptron (MLP) learnt with *backpropagation* algorithm. We include this

model for comparison purposes because, as it is showed in previous work [10], it appears to be the best machine-learning model to foresee the ultimate tensile strength.

– **Testing the model:** For each classifier, we evaluated the percent of correctly classified instances and the area under the Receiver Operating Characteristic (ROC) that establishes the relation between false negatives and false positives [23].

4 Results

As we mentioned before, we have evaluated the classifiers in terms of prediction accuracy and the area under the ROC curve. In this way, Table 1 illustrates the obtained results in terms of prediction accuracy. Using the full original dataset of 889 evidences we can achieve an 86.84% of accuracy level. *Random forest with 250 trees* outperformed the rest of classifiers. On one hand, each of the random forest are better classifiers than the J48. Although both of them are based in decision trees, the first one is the best classifier and the second one is nearly the worst classifier. On the other hand, the deviation between all random forest is really small, but we can consider that the random forest with 250 trees like a local maximum.

Table 1. Results in terms of accuracy

Machine-learning Model	**Accuracy** (%)
Decision Tree: RandomForest with 250 trees	86.84
Decision Tree: RandomForest with 200 trees	86.77
Decision Tree: RandomForest with 300 trees	86.76
Decision Tree: RandomForest with 150 trees	86.68
Decision Tree: RandomForest with 100 trees	86.55
Decision Tree: RandomForest with 50 trees	86.53
Decision Tree: RandomForest with 10 trees	85.40
Artificial Neural Network: Multilayer Perceptron	84.23
SVM with Normalised Polynomial Kernel	83.78
SVM with Polynomial Kernel	82.07
SVM with Radial Basis Function Kernel	81.71
Decision Tree: J48	81.66
SVM with Pearson VII universal kernel	80.75

Notwithstanding, despite random forests have achieved better accuracy levels than the ANN, SVM-based classifiers could not overcome the ANN. Surprisingly, *SVM*s did not achieve as good results as we thought in beforehand because of their impressive results in information retrieval [24]. Hence, we can leave aside the SVM and J48 because they do not bring any improvement in the prediction of the ultimate tensile strength.

Furthermore, Table 2 shows the area under the ROC curve (AUC). In this way, the obtained results in terms of AUC are similar to the ones of prediction

Table 2. Results in terms of area under the ROC curve

Machine-Learning Model	Area under ROC curve
Decision Tree: RandomForest with 250 trees	0.9206
Decision Tree: RandomForest with 300 trees	0.9206
Decision Tree: RandomForest with 200 trees	0.9202
Decision Tree: RandomForest with 150 trees	0.9197
Decision Tree: RandomForest with 100 trees	0.9182
Decision Tree: RandomForest with 50 trees	0.9155
Decision Tree: RandomForest with 10 trees	0.8936
Artificial Neural Network: Multilayer Perceptron	0.8594
Decision Tree: J48	0.7626
SVM with Normalised Polynomial Kernel	0.7524
SVM with Polynomial Kernel	0.7445
SVM with Radial Basis Function Kernel	0.7151
SVM with Pearson VII universal kernel	0.6570

accuracy and the *random forest with 250 trees* also outperformed the rest of algorithms. Although all of them accomplish acceptable values (they exceed the line of no-discrimination), random forests outshine the other classifiers.

Actually, even the system has not achieved a 100% accuracy level, it has interesting results for being used in a high-precision foundry (more than 86%). In this way, we reduce in a significant manner the cost and the duration of the actual testing methods. Remarkably, the outstanding results achieved by the random forest with 250 trees show that it can be used in a similar way as we have used the Bayesian networks or artificial neural networks in previous works.

In addition, using this kind of predictive tool, the behaviour of the foundry workers can be the following one: when the system detects that the apparition's probability of an inadequate value of the ultimate tensile strength is very high, the operator may change the factors to produce this casting within the reference or change the whole reference (skipping the cost of having to re-manufacture it one more time). Also, the foundry workers and engineers can test the new configuration of a casting before they make it at foundry.

5 Conclusions

The ultimate tensile strength is the capacity of a metal to resist deformation when subject to a certain load. When a manufactured piece does not resist a certain threshold, it must be discarded in order to avoid breaking afterwards. Foreseeing the value of ultimate tensile strength renders as one of the hardest issues in foundry production, due to many different circumstances and variables that are involved in the casting process.

Our previous research [2,11] pioneers the application of Artificial Intelligence to the prediction of microshrinkages. Here, we have extended that model to the prediction of mechanical properties [3]. Later, we have focused on comparing *machine-learning* classifiers used for the prediction of ultimate tensile strength

[10]. Specifically in this research, we have included and adapted to our particular problem domain two classifiers that have been used widely in similar issues. All of them behave well, but random forests outperform the rest of the classifiers. Still, the ability of Bayesian theory and specifically, the sensitivity module (developed in [3]) cannot be ignored since it is an effective method that adds a decision support system for the operators in the foundry plant.

In addition, as we noticed in previous works [3,10,11], there are some irregularities in the data that may alter the outcome rendering it not as effective as it should. More accurately, these inconsistencies appear because the data acquisition is performed in a manual fashion.

Accordingly, the future development of this predictive tool will be oriented in five main directions. First, we plan to extend our analysis to the prediction of other defects in order to develop a global system 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. Third, we plan to integrate the best classifiers in a meta-classifier which will work as a black box combining all partial results to predict any defect. Fourth, we plan to employ some techniques (e.g. Bayesian compression) to give more relevance to the newer evidences than to the older ones. And, finally, we plan to test a preprocessing step to reduce the irregularities in the data.

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