Mechanical Properties Prediction in High-Precision Foundry Production

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***Abstract*—Mechanical properties are the attributes of a metal to withstand several forces and tensions. Specifically, *ultimate tensile strength* is the force a material can resist until it breaks. The only way to examine this mechanical property is the employment of destructive inspections that renders the casting invalid with the subsequent cost increment. In a previous work we showed that modelling the foundry process 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 value of ultimate tensile strength). Against this background, we present here the first ultimate tensile strength prediction system that, upon the basis of a Bayesian network, is able to foresee the values of this property in order to correct it before the casting is made. Further, we have tested the accuracy and error rate of the system with data of a real foundry.**

I. Introduction

Foundry is considered to be one of the main driving forces of modern economy. In this way, it supplies necessary pieces to automotive, naval, aeronautic or weapon industries, for instance. As one may think, high-precision is the key to develop smaller, better, and more precise parts of crucial pieces but such accuracy entails also other risks, since the tiniest error may become fatal. Think, for instance, that high-precision foundry casts components of car brakes, aeroplane turbines or windmill propellers.

Therefore, there are very strict quality standards to assure the exclusion of faulty pieces. Unfortunately, these controls are all performed *ex-post*, when the production effort is already done. In this sense, error prediction, on the one hand, allows avoiding the production of defective items to fulfil quality standards, and on the other, it also helps not to squander resources on that activity (i.e. helps saving money).

In previous works [1] [2], we presented a research on the prediction of a defect known as *microshrinkage*. Here we focus on the prediction of the mechanical properties of the casting metal, which allows to infer the so-called *ultimate tensile strength*. Moreover, ultimate tensile strength is the maximum stress any material can withstand when subjected to tension; in other words, the strength a material is able to resist until it breaks. Hence, assuring that all pieces manufactured reach a certain ultimate tensile strength threshold is an essential goal of the quality tests. As in our previous work, we apply the inference ability of Bayesian Networks [3] in order to achieve an effective prediction. Bayesian networks are probabilistic models 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, successful applications of Bayesian networks include for instance email classification for spam detection [4], failure detection in industrial production lines [5] [6], weather forecasting [7] [8], intrusion detection over IP networks [9] [10] or reconstruction of traffic accidents [11] [12]. In all cases, the respective target problem is modelled as a constellation of interconnected variables whose output is always the result of the prediction (e.g. spam found, failure detected, intrusion noticed and so on). Similarly, the production process of a foundry is perfectly suitable to be modelled as system of variables whose behaviour may influence in one way or another the mechanical properties of the obtained piece.

Against this background, this paper advances the state of the art in two main ways. First, we present here, for the first time, a Bayesian-network-based mechanical properties prediction system that is especially designed to calculate before producing it the ultimate tensile strength of the manufactured piece. Second, we introduce here a methodology to test the accuracy and error rate of a Bayesian network for the prediction of the ultimate tensile strength in foundry processes.

The remainder of the paper is organised as follows. Section II details mechanical properties of iron castings, focusing on the ultimate tensile strength. Section III introduces in deeper detail the concept of a Bayesian network and presents the creation method of the one tailored to iron foundries. Section IV describes the experiments performed and section V examines the obtained results and explains feasible enhancements. Section VI discusses related work. Finally, section VII concludes and outlines the avenues of future work.

II. Mechanical Properties of Iron Castings

Several factors, for instance the extreme conditions in which it is carried out, make the foundry process very complex. Starting from the raw material to the manufactured item, this procedure involves numerous stages, some of which may be performed in parallel. More accurately, when it comes to iron ductile castings, this process presents the following phases:

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- **Melting and pouring:** The raw metals are melt, mixed and poured onto the sand shapes.
- **Moulding:** The moulding machine forms and prepares the sand moulds.
- **Cooling:** The solidification of the castings is controlled in the cooling lines until this process is finished.

Fig. 1 shows the moulding and cooling phases. Once the raw material is melt, it is poured onto the moulds (made out of sand mixed in the sand-mill) and shaped in (1). The cooling lines (2) accelerate the natural cooling process of the castings and, when they are properly solidified, the sand moulds are detached from them and return to the sand-mill so the sand can be reused to mould further castings.

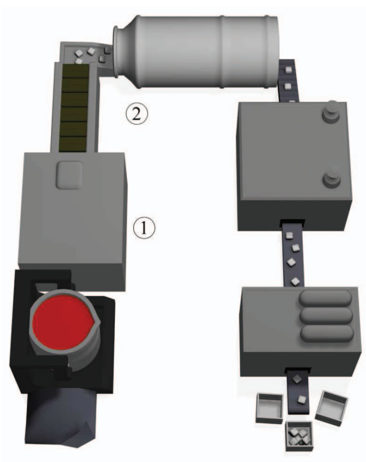

Fig. 1. Moulding and cooling in the casting production

After these phases, 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 know how mechanical properties affect to iron castings [13], since it directly affects the quality of the final piece. Specifically, the most important mechanical properties of foundry materials are the following ones[14]:

- **Strength:** it is the property that enables a metal to resist deformation under load. There are many kinds of strength such as ultimate strength and ultimate tensile strength (UTS).
- **Hardness:** it is the property to resist permanent indentation.
- **Toughness:** it is the property that enables a material to withstand shock and to be deformed without rupturing. This property is considered as a combination as strength and plasticity.
- **Resilience:** it is the property of a material to absorb energy when it is deformed elastically.
- **Elasticity:** it is the ability of a material to return to its original shape after the load is removed.
- **Plasticity:** it is the ability of a material to deform permanently without breaking or rupturing. This property is the opposite of strength.
- **Brittleness:** it is the opposite of plasticity. A brittle metal is one that breaks or shatters before it deforms. Generally, brittle metals have a high value in compressive strength but a low value in tensile strength.
- **Ductility:** it is the property that enables a material to stretch, bend or twist without cracking or breaking.
- **Malleability:** in comparison with ductility, it is the property that enables a material to deform by compressive forces without developing defects. A malleable material can be stamped, hammered, forged, pressed or rolled into thin sheets.

In order to establish these mechanical properties, scientists have to test the materials in a laboratory using common or standard procedures (e.g. ASTM standards [15][16]). Unfortunately, the only way to examine the mechanical properties is the employment of destructive inspections. Moreover, the process requires suitable devices, specialised staff and quite a long time to analyse the materials.

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

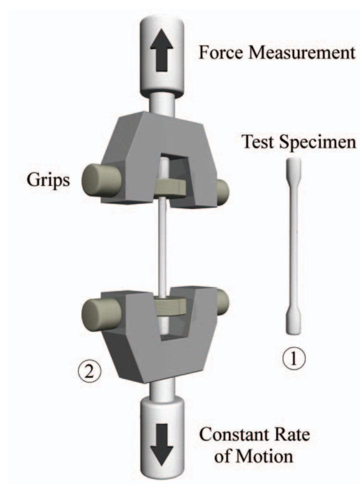

Fig. 2. Ultimate Tensile Strength Test

Furthermore, there are some variables that may influence the mechanical properties of the metal during the foundry process, such as the composition [17], the size of the casting, the cooling speed and thermal treatment [13][18]. The system must take into account all of them in order to issue a prediction on those mechanical properties. In this way, as detailed in section III, the Bayesian network used in our experiments is composed of about 25 variables.

III. Bayesian-Network-Based UTS Prediction

The research on cause-consequence relationships was pioneered by Reverend Thomas Bayes [19], and his main work is known as the "Bayes theorem" in his honour. According to its classical formulation, given two events A and B, the conditional probability $P(A|B)$ that A occurs if B occurs can be obtained if we know the probability that A occurs, P(A), the probability that B occurs, $P(B)$, and the conditional probability of B given A, $P(B|A)$ (as shown in equation 1):

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)} \tag{1}$$

Extending this model, Bayesian networks are probabilistic models for multivariate analysis. We can represent a Bayesian network as an acyclic directed graph and the probability distribution function associated to that graph [20]. On the one hand, the graphical model represents the set of probabilistic relationships among the collection of variables modelling a particular problem. On the other hand, the probability function illustrates the strength of these relationships or edges in the graph.

We use this kind of model for several activities, for example, machine learning based on historical data, pattern matching over ambiguous or incomplete data , data mining for relationship discovery and inference of non-observable variables given the rest of the set [21]. In particular, this inference capability fits to our experiments. These capability represents a semantical super-set of those expert systems based on rule chaining, both for forward and backward style (in fact, Bayesian models allow a third further kind of inference, that is known as explanation or justification [20]). Moreover, a Bayesian network can grow extending its knowledge base with new evidences without reducing its performance level [20] whilst adapts to the problem and maintain an updated procedure.

To our experiment, the most important ability of Bayesian networks is their capability of inferring the probability that a certain hypothesis becomes true, out of the values that the variables forming the Bayesian network take. In this way, we have modelled the main factors that are relevant to mechanics properties of metals as a Bayesian network and the value of ultimate tensile strength as the hypothesis to validate. The creation and setting-up of our Bayesian network comprises the following phases:

1) **Causal probability network obtaining:** First of all, we have to define the variable that is going to be the output and the result. As already mentioned, for our experiment, it is the probability of the range of values for the ultimate tensile strength. Subsequently, we complete the Bayesian network with the set of input variables (listed in the section II). The Bayesian network associates a probability table to each variable and calculates the probability values taking into account interdependencies of the variables. In this stage, the collaboration of a human expert is mandatory and really important.
2) **Training data selection:** In order to obtain a significant sample of real data, we have created a dynamic database with the aforementioned input and output data and recorded values during a year (see section IV for a description of its training). From each controlled production series, we select representative groups of moulds, registering values of the variables. Moreover, the database has the values of the ultimate tensile strength, the real values which have been obtained with destructive inspections.
3) **Structural learning:** After the Bayesian network defined in stage 1 is trained as stage 2 shows, the initial structure of the Bayesian network is ready. The goal of the structural learning is the refinement of this model. In particular, the PC-Algorithm [22] is used here to achieve the structure of causal and/or correlative relationships between given variables from the data. In other words, the PC-Algorithm uses the traffic sample data to define the Bayesian model, representing the whole set of dependence and independence relationships among detection parameters. If we know that some relationships between the variables are required to be present in the graph, we can apply the NPC-Algorithm [23]. The NPC-Algorithm permits to define these initial relationships known as *necessary path conditions*. Due to its high requirements in terms of computational and temporal resources, this phase is usually performed in an off-line manner.
4) **Parametrical learning:** Fed with new data, the Bayesian network obtains the probabilities associated to new samples and, subsequently, it recalculates the whole probability table modifying in this way its knowledge base in a continuous learning process. This phase allows a further refinement of the structure obtained in phase 3 and generally simplifies the Bayesian network. It is worth mentioning, in our experiments, we start with 25 variables that are related between and we do not discard any of them. In this phase, we use Expectation - Maximisation Algorithm (EM-Algorithm) [23].
5) **Bayesian inference:** Inference engines use Bayesian evidence propagation to, based on an existing knowledge model, calculate the value of a certain variable. In this way, we use the Lauritzen and Spiegelhalter method for conclusion inference over junction trees, since it is slightly more efficient than any other in terms of response time [20]. Thereby, already working in real time, the input variables of future castings are analysed by this method in order to define the later probability of the value of the ultimate tensile strength.

Finally, we have developed an application that runs on top of the Bayesian network: the so-called *sensitivity module* (SM). The SM [24] studies the different values that each variable adopts in order to trace the influence of such values in the apparition of a range of the ultimate tensile strength. Note that a variable may represent, for example, the use of one or another product in a certain phase of the process, applying one certain methodology or not, and so on. In this way, if a variable shows the amount of magnesium used and there are three choices, the sensitivity module will determine which one is the most convenient one in terms of obtaining a certain

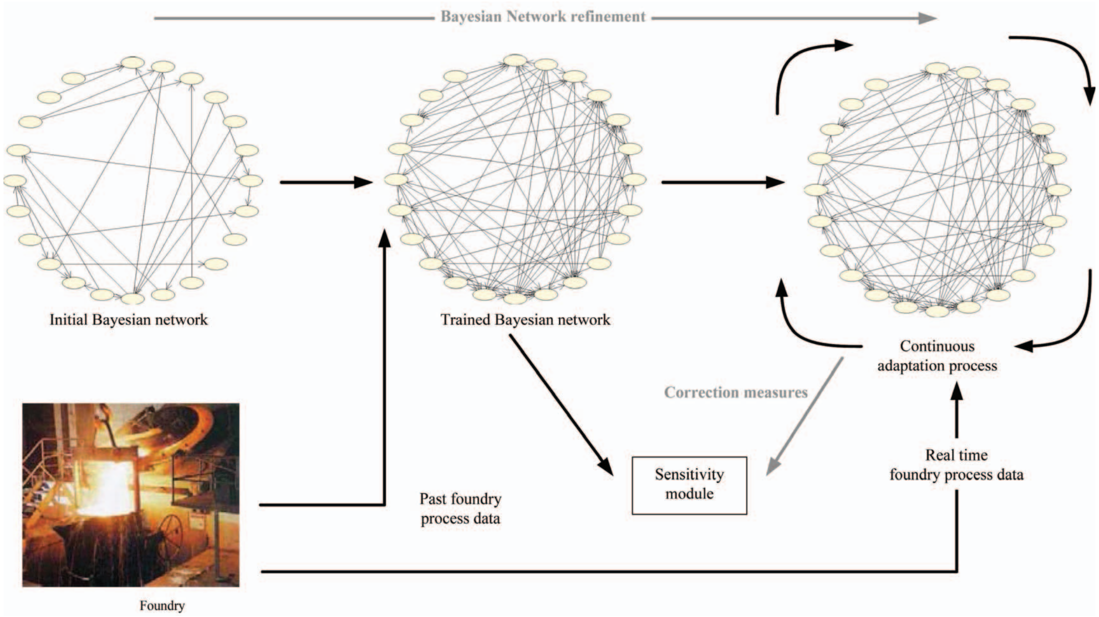

Fig. 3. Life-process of the Bayesian network

value of the ultimate tensile strength. This is, the SM evaluates the results obtained by the Bayesian network and calculates the causal relationship between each amount of magnesium and the probability that a range of ultimate tensile strength appears. Hence, the SM can recommend using only the best value to obtain a concrete range of ultimate tensile strength. In conclusion, the sensitivity module helps tuning up the foundry process by suggesting the most suited values of the variables.

IV. 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. Note that, as aforementioned, the only way to examine the mechanical properties is the employment of destructive inspections, therefore, the evaluation must be done after the production is done.

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 ultimate tensile strength must be rejected.

In these experiments, the Bayesian network has 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, with the results of the destructive inspection from 889 castings (note that each reference may involve several castings or pieces) performed in beforehand. Still, the Bayesian network shows a different performance depending on the quality of the training. Therefore, we have examined it with datasets of diverse sizes (n). In this way, we have carried out experiments with $n = 100$, $n = 200$, $n = 300$, $n = 400$, $n = 500$, $n = 600$, $n = 700$, $n = 800$, and with the full original dataset ($n = 889$). The testing procedure was always the same: the Bayesian network was trained with the 66% of the dataset (e.g. 66 castings with n=100) and then, it issued it predictions on the rest of the dataset (e.g. 34 castings with n=100). Moreover, we followed the next methodology in order to evaluate properly the Bayesian network:

- **Cross validation:** For each different n we have performed a *k-fold cross validation* [25] 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 made the learning phase with the PC-Algorithm [22] with each training dataset.
- **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 size of the testing dataset m) with mean absolute error (MAE) (shown in equation 2).

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

Similarly, we have used root mean square error (RMSE) (shown in equation 3)

$$RMSE(X,Y) = \frac{1}{m} \cdot \sqrt{\sum_{i=1}^{m} (X_i - Y_i)^2} \tag{3}$$

V. Results

Fig. 4 shows the obtained results in terms of prediction accuracy. In this way, with a size of 100 castings for the dataset the Bayesian network predicted correctly only the 75% of the castings; this means that it was not able to build a proper representation of the data with $n = 100$.

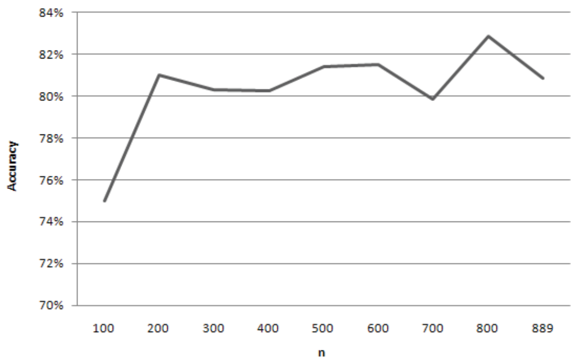

Fig. 4. Accuracy of Bayesian Networks

Doubling the size of the dataset improves the accuracy of the model drastically, and from that on, all sizes perform good results. Moreover, the experiments showed the best accuracy results with a dataset size of 800 castings. Please note that the data adquisition is made manually. Hence, errors may appear causing noise. Further, Fig. 5 shows the mean absolute error and the root mean square error. The experiments remarked that the best results are also achieved with a size of 800 castings.

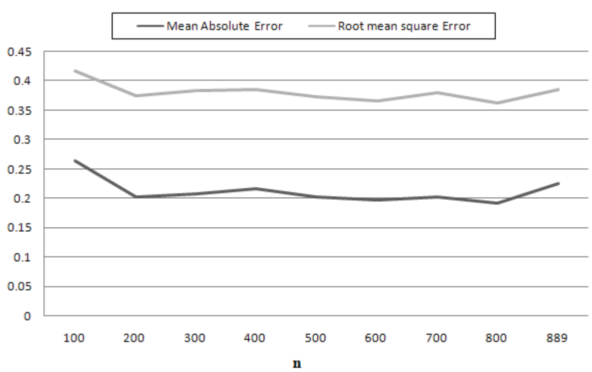

Fig. 5. Error of Bayesian Networks

Actually, even the system has not reached a 100% accuracy level, it has interesting results for being used in a high-precision foundry (more or less 80%), similar to those achieved with microshrinkage prediction in [1]. In this way, we reduce in a significative manner the cost and the duration of the actual testing methods, apart from providing an effective *ex-ante* method.

Moreover, all tests were started from 0. This is, the Bayesian network had to build its knowledge base all times from scratch, which is an unusual situation. Indeed, the Bayesian network is designed to work in a continuous fashion and, in this way, it constantly extends and enhances its knowledge base, improving its prediction. Still, this fact can also become a problem if we introduce new references that not have been handled before. The information about these new references has too less significance if we compare to older samples, and therefore, predictions about new references of castings will not be as precise as they should be. There are two techniques that contribute to minimise this phenomenon [1]. The first one consists of using *fading factors* that vanish the importance of old information as new data arrives [26]. The second one, known as *Bayesian compression* [27], interpolates existing evidences reducing them, so new evidences easily gain importance [28].

Finally, our experience shows that the behaviour of the system can be outperformed in the following way: when the system detects that the probability of a bad value of the ultimate tensile strength to appear is very high, the operator may change the factors to produce another reference (and, thus, to skip the cost of having to re-manufacture it again) and try it later.

VI. Related Work

Lately, the problem of predicting mechanical properties has been tackled by using machine learning methods [29] [30] [31]. These works presented similar results to our experiments but they are inefficient due to two main reasons.

First, they take into account variables that, according to our results, are unimportant or, vice versa, do not include important variables in their analysis. Still, using the aforementioned capability of sorting the relevance of the variables of the sensitivity module, we have built a Bayesian Network that achieved the same results that the network built without using it. Second, several of them use genetic algorithms that had a high computational cost.

One of the most used methods is the application of Neural Networks in several aspects, for instance, classifying foundry pieces [32], optimising casting parameters [33], detection of causes of casting defects [34] and in other problems [35]. Nevertheless, Bayesian networks are used as previous methods in Bayesian Neural networks methodology (i.e. predicting the ferrite number in stainless steel [36]). Despite these experiments, to our knowledge there is no single published research on the prediction of mechanical properties, specially the ultimate tensile strength, with Bayesian networks. The only similar research is the prediction of microshrinkages in high-precision foundry ([1] and [2]), which obtained analogous results to the work we present here.

VII. Conclusion

The ultimate tensile strength shows the capacity of a metal to resist deformation under load. If a manufactured piece does not exceed a certain threshold, it must be discarded in order to avoid breaking afterwards. Predicting the level of ultimate tensile strength is one of the most difficult issues in foundry, since there are many different circumstances and variables involved during the casting process that determine it.

In this paper, we present a new Bayesian-network-based tool that allows to foresee this level of ultimate tensile strength.

Moreover, this prediction system enables the integration of the already existing microshrinkage prediction tool [1], [2].

We have tested this tool in terms of accuracy and error rate using a dataset resultant of previous destructive inspections of diverse castings. Further, we have used different sizes for the aforementioned dataset in order to study how the system behaves whilst increasing the training set size. Moreover, these experiments showed us that the size of the training set must be representative enough to build correct representation of the problem we deal with. In this way, experiments have shown that Bayesian Networks can predict the level of ultimate tensile strength of the evaluated casting with an optimal accuracy of 82.88% for dataset size of $n = 800$, which is a better result than with the full size of the original dataset ($n = 889$).

The future development of this predictive tool is oriented in two main directions. First, we plan to extend our analysis to the prediction of other mechanical properties (such as tensile elongation and tensile modulus of elasticity) in order to develop a global network of mechanical properties analysis. Second, we plan to integrate this tool with the existing microshrinkage prediction system.

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