In: Structural Steel and Castings: Shapes and Standards... ISBN: 978-1-61728-104-4
Editor: Lena M. Becker

Chapter 9

MACHINE-LEARNING-BASED DEFECT PREDICTION IN HIGH-PRECISION FOUNDRY PRODUCTION

Igor Santos, Javier Nieves, Pablo G. Bringas and Yoseba K. Penya*
University of Deusto, Bilbao, Spain

Keywords: Defect forecasting, machine-learning, data-mining.

1. Introduction

Foundry has evolved from the ancient magic-surrounded activity it used to be, to become a key industry that maintains the world as we know it. Thereby, it supplies major pieces to another industries such as, automotive, naval, aeronautic, weapon and so on. As one may think, many of these pieces play key roles in the final product as in the case of brakes, aeroplane components or wind energy castings and this reason imposes high-quality standards: the tiniest defect may become fatal.

Therefore, there are very strict quality standards to assure the exclusion of faulty pieces. Unfortunately, these controls are all performed in an ex-post manner, when the production effort is already done. In this sense, error prediction, firstly, allows avoiding the production of defective items to fulfil quality standards, and secondly, it also helps not to squander resources on that activity.

Nowadays, 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 results in an a posteriori fashion.

On one hand, microshrinkage, 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 [2, 3]. The biggest problem associated to microshrinkages is that pieces flawed with this defect must be discarded. Moreover, caused 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

*Email address: {isantos, javier.nieves, pablo.garcia.bringas, yoseba.penya}@deusto.es

stipulate that all castings of that production series must be X-ray-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 remelt, new production process and still no guaranty that this time is going to work).

On the other hand, mechanical properties are the ability of the material of a piece to take several forces and tensions. In this chapter we focus on the so-called *ultimate tensile strength* that is the force that a casting can withstand until it breaks. Therefore, the foundry castings that are manufactured have to reach a certain value or threshold of ultimate tensile strength in order to pass the strict quality tests. More accurately, current standard procedures to determine that value are the employment of destructive inspections. Unfortunately, these procedures make the piece useless after the inspection and thus, as happens with microshrinkages, they also incur a cost increment.

Hence, providing effective ex-ante methods can help to increase the quality standards and to save resources in the process (i.e. saving money). To this extent, *machine-learning* classifiers have been applied in domains alike with outstanding results, for instance, neural networks [4], Bayesian 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]. Moreover, successful applications of Bayesian networks include for instance email classification for spam detection [10], failure detection in industrial production lines [11] [12], weather forecasting [13] [14], intrusion detection over IP networks [15] [16] or reconstruction of traffic accidents [17] [18]. Similarly, K-nearest neighbour algorithm, despite its simplicity, has been applied for instance to visual category recognition [19], weather forecasting [20], malware detection [21] or image retrieval [22].

Against this background, this chapter advances the state of the art in two main ways. First, we propose a methodology to adapt machine learning classifiers to the prediction of microshrinkages or ultimate tensile strength and we describe the method for training them. Second, we evaluate the classifiers with a historical dataset from a real foundry process in order to compare the accuracy and suitability of each method.

The remainder of this chapter is organised as follows. Section 2. discusses related work. Section 3. details the foundry process of iron castings. Section 5. introduces and describes the *machine-learning algorithms* we tailor to iron foundries. Section 6. describes the experiments performed and examines the obtained results and explains feasible enhancements. Finally, section 7. 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 [23]. Similarly, successful experiments involving K-nearest neighbour algorithm include fault detection of semiconductor manufacturing processes [24].

In a verge closer to our view, neural networks have been used in several works, for instance, classifying foundry pieces [25], optimising casting parameters [26], detection of causes of casting defects [27] and in other problems [28]. Nevertheless, Bayesian networks are used as previous methods in Bayesian neural networks methodology (i.e. predicting the ferrite number in stainless steel [29]). In addition, K-nearest neighbour algorithm and artificial neural networks have been applied for enhance quality of steel [30] that achieves an overall root mean square error of 0.38 (a comparison between their results and ours can be further analysed in section 6.).

The good results obtained for these works have encouraged us to tailor these approaches into our concrete problem domain.

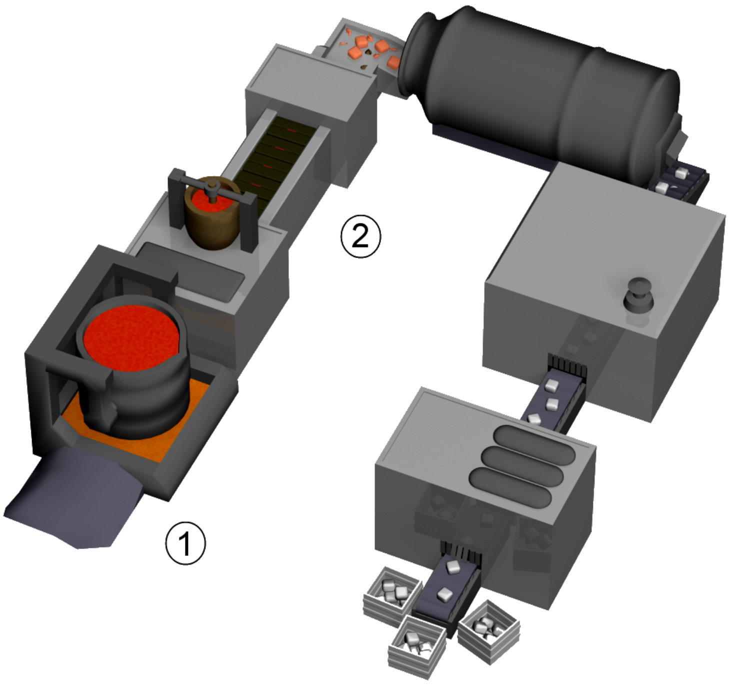

Figure 1. Moulding and cooling in the casting production

3. Foundry Process

There are several factors that make foundry production a very complex process, such as, the extreme conditions in which it is performed. In this way, starting from the raw material to the manufactured item, this procedure involves numerous phases, some of which may be performed in parallel. More accurately, when it refers to iron ductile castings, this process presents the following phases:

- **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.

Figure 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. 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.

4. Defects on Foundry Processes

4.1. Microshinkages

Microshrinkages appear during the cooling process of the metal but are only visible once 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 casting's hardness and, in the cases faced here (where the casting is a part of a very sensitive piece), rendering the piece useless [3, 31]. Unfortunately, the only way to examine finished parts is the employment of non-destructive inspections. In this way, the most usual 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, postproduction inspection is not an economical alternative to the pre-production detection of microshrinkages.

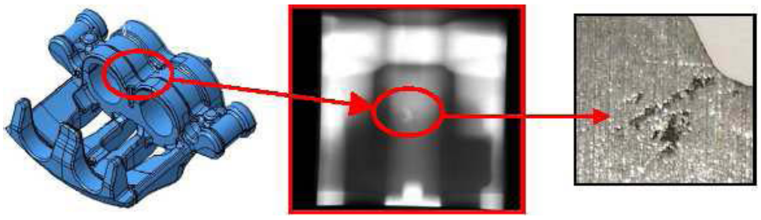

Figure 2. Computer simulation of microshrinkage formation in a double-cylinder break calliper.

Figure 2 shows one of the castings examined here, the calliper of a front double-cylinder brake that, as exposed in section IV, tends to present microshrinkages. Figure 3 illustrates the gradual formation of a microshrinkage as the piece is cooling down. This computer simulation shows a transversal cut of the casting and the risk that the defect appears (the closer to red, the higher the risk). The first two images illustrate the solidification process and the last one shows the final presence of the microshrinkage.

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:**

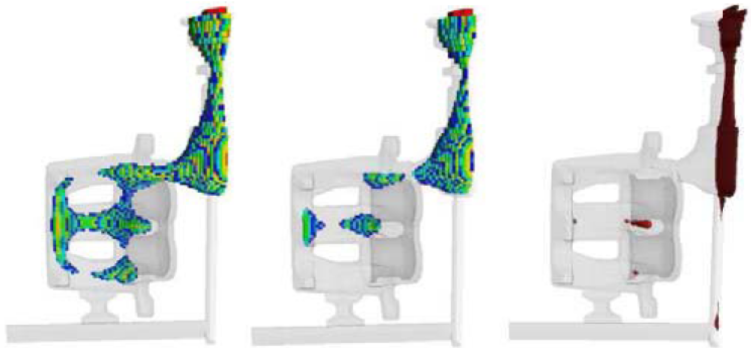

Figure 3. Formation of the microshinkage in the double-cylinder break calliper.

- *Composition:* Type of treatment, inoculation and charges.
- *Nucleation potential and melt quality:* Obtained by means of a thermal analysis program [32].
- *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 [33].

Furthermore, there are some variables that may influence the apparition of second contraction during the foundry process, such as the composition [34], the size of the casting, the cooling speed and thermal treatment [35] [36]. 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.

4.2. Mechanical Propierties

Once the phases shown in section 3. have been completed, the resultant casting is subject to forces (loads). Engineers have to calculate the value of these forces and how the material deforms or breaks as a function of applied load, time or other conditions. Hence, it is a very important theme knowing how mechanical properties affect to iron castings [35], since they directly affect the quality of the final piece. More accurately, the most important mechanical properties of foundry materials are the following ones [37]:

- **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.
- **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.

Furthermore, there are common or standard procedures (i.e. ASTM standards [38, 39]) for testing the value of mechanical properties of the materials in a laboratory. Unfortunately, they need to use destructive inspections and they are *ex-post* (i.e. performed after production). Moreover, the process demand appropriate instruments, specialised staff and time resources in order to inspect 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 Figure 4). 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.

Moreover, there are some variables that may influence the mechanical properties of the metal during the foundry process, such as the composition [34], the size of the casting, the cooling speed and thermal treatment [35, 36]. 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 models used in our experiments are composed of about 25 variables.

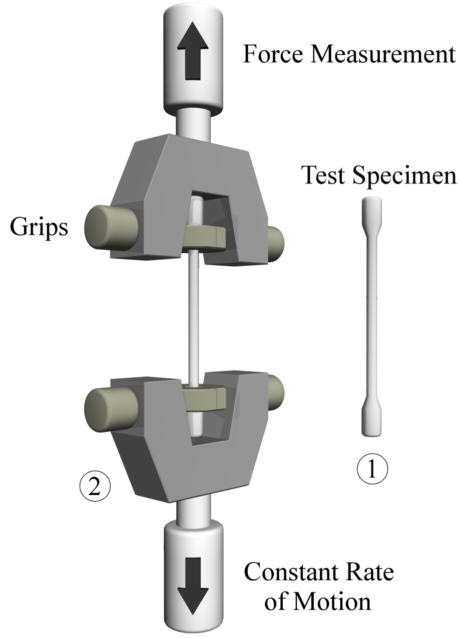

Figure 4. Ultimate Tensile Strength Test

5. Machine-learning Classifiers

5.1. Bayesian Networks

The research on cause-consequence relationships was pioneered by Reverend Thomas Bayes [40], 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 [41]. 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 [42]. 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 [41]). Moreover, a Bayesian network can grow extending its knowledge base with new evidences without reducing its performance level [41] whilst adapts to the problem and maintain an updated procedure.

To our needs, the most important ability of Bayesian networks is their capability of inferring the probability that a certain hypothesis becomes true (i.e. the probability of microshrinkage apparition).

Besides, the sensitive module [43] (SM), that we used for both microshrinakages and mechanical properties [44], provided a decision support system for the operators in the foundry rely on Bayesian theory. Specifically, SM 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. 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.

5.2. K-Nearest Neighbours

The *K- nearest neighbour* [6] algorithm is one of the simplest supervised machine learning algorithms for classifying instances. This algorithm is based on the class of the most nearest instances of an unknown instance.

Specifically, the training phase of this algorithm comprises representing a set of training data instances $S = s_1, s_2, .., s_m$ in a $n-dimensional$ space where n is the amount of variables for each instance (i.e. in our case the variables of the casting production).

Furthermore, the classification phase of an unknown instance (whose class is not known) is performed by measuring the distance between the training instances and the unknown instance. In this way, establishing the distance between two points X and Y in a $n-dimensional$ space, can be achieved by using any distance measure, in our case we used Euclidean distance (shown in equation 2).

$$\sqrt{\sum_{i=0}^{n}(X_i - Y_i)^2} \tag{2}$$

Finally, there are several ways to choose the class of the unknown instance, the most used technique is to classify the unknown instance as the most common class amongst the *K-nearest neighbours*.

5.3. Artificial Neural Networks

Artificial Neural Networks (ANN) is a machine learning model that simulates the behaviour of neurons in the human brain [4]. Formally, a neuronal network consists on interconected neurons. In this way, the activation of a neuron depends on its set of inputs, where y_i is the activation of the current neuron, f_i is the activation function, $W_{j,i}$ is the weight of the neuron and a_j is the activation of the input neuron (shown in equation 3).

$$y_i = f_i\left(\sum_{j=0}^{n} W_{j,i} \cdot a_j\right) \tag{3}$$

More accurately, *Multi-Layer Perceptron* (MLP) is a kind of artificial neural network model of simple neurons called perceptrons that are structured in layers. The layers can be classified as *input layers*, *hidden layers* and *output layer*. We perform the training of the model using *backpropagation algorithm* [45] that calculates the weights W_j of the activation function for each neuron.

6. Experiments and Results

6.1. General Methodology

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 on prediction of microshrinkages and ultimate tensile strength. Note that, as aforementioned, microshrinkages are detected by the employment of X-Ray inspections, and, in a similar vein, the only way to examine the mechanical properties is the employment of destructive inspections. Therefore, the evaluation must be performed 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 microshrinkages or an invalid ultimate tensile strength must be rejected.

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

- **Cross validation:** We have performed a *k-fold cross validation* [46] 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 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:

  - *Bayesian networks:* In order to train Bayesian networks we have used different structural learning algorithms; K2 [47], Hill Climber [48] and Tree Augmented Naive (TAN) [49]. Moreover, we have also performed experiments with a Naïve Bayes Classifier.
  - *K-nearest Neighbour:* For *knn* we have performed experiments with $k = 1$, $k = 2$, $k = 3$, $k = 4$, and $k = 5$.
  - *Artificial neural networks:* We have used a Multilayer Perceptron (MLP) learned with *backpropagation* algorithm.

- **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 4).

$$MAE(X,Y) = \sum_{i=1}^{m} \frac{|X_i - Y_i|}{m} \tag{4}$$

Similarly, we have used root mean square error (RMSE) (shown in equation 5)

$$RMSE(X,Y) = \frac{1}{m} \cdot \sqrt{\sum_{i=1}^{m} (X_i - Y_i)^2} \tag{5}$$

6.2. Microshrinkage Experiments

Figure 5 shows the obtained results in terms of prediction accuracy and Figure 6 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 Naïve seem more suitable if we focus on 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.

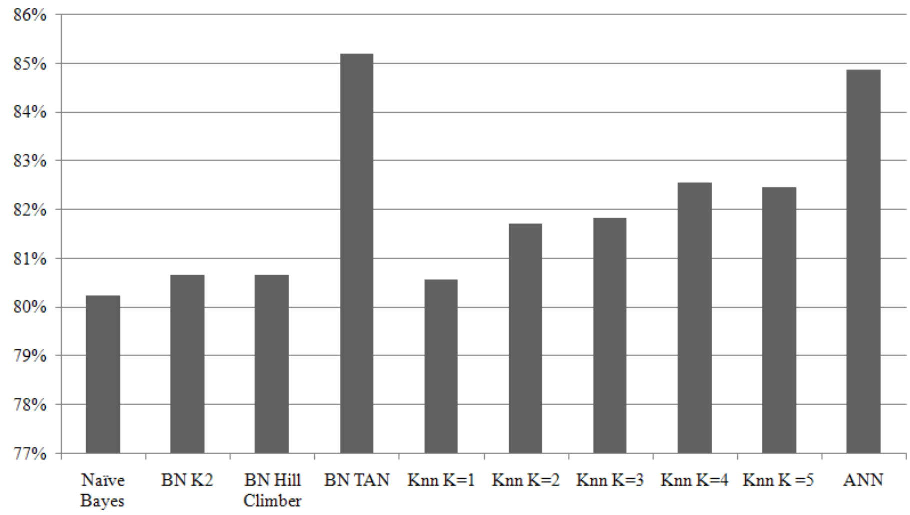

Figure 5. Accuracy of Evaluated Classifiers

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 on the resemblance between the instances. Therefore, it behaves worse than more robust methods such as ANN and Bayesian networks.

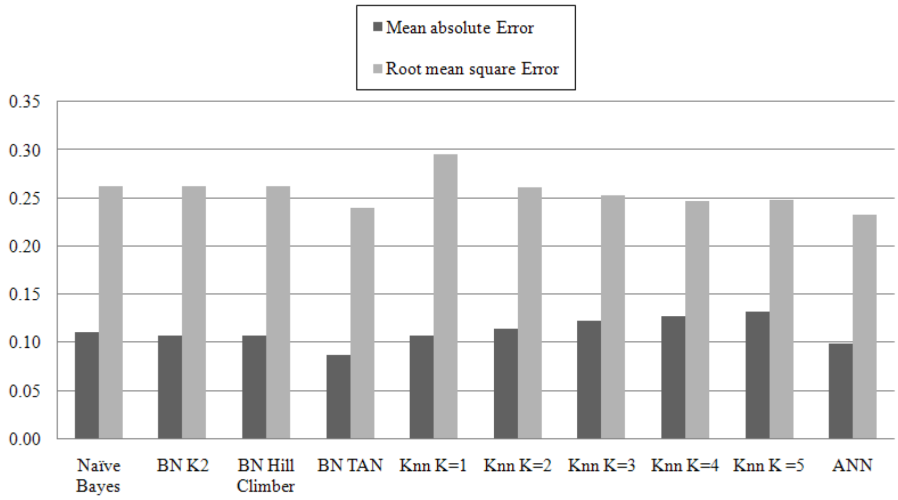

Figure 6. Error Rate of Evaluated Classifiers

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 a previous work [50]. Thereby, 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.

6.3. Ultimate Tensile Strength Experiments

As we mentioned before, we evaluated the classifiers in terms of prediction accuracy and error (i.e. MAE and RSME). In this experiments we have also performed an analysis of the optimal training dataset size. Therefore we have performed the experiments for the following training sizes n: $n = 100$, $n = 200$, $n = 300$, $n = 400$, $n = 500$, $n = 600$, $n = 700$, $n = 800$ and $n = 889$.

In this way, Figure 7 shows the obtained results in terms of prediction accuracy. For a size of the training dataset of 100 the overall prediction of the *machine-learning classifiers* is low, however, Bayesian networks trained with *Hill Climbing* outperformed the rest of classifiers with a prediction accuracy of 81.82%. Despite these results, this approach for Bayesian networks did not perform well when increasing the size of the dataset. On the other hand, the rest of classifiers, obtained their best results for a training size between 700 and 800 instances and not for the whole training dataset ($n = 889$) where there is an interesting accuracy reduction. This fact may be result of the data acquiring phase that is performed manually and, thus, it is subject to numerous errors that can include noise in the dataset. Therefore, techniques for reducing the noise of the dataset such as Principal Component Analysis [51] will be studied in further work.

More accurately, the algorithms showed quite different performances. In this way, *k-nearest neighbour* did it surprisingly well for being a lazy algorithm. Specifically, for a value of $k = 1$, *k-nearest neighbour* achieved the best results and the second best classifier

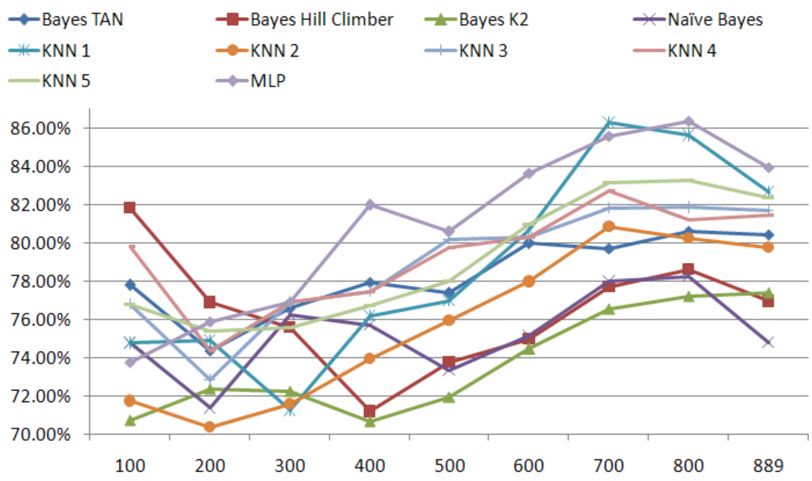

Figure 7. Accuracy of the evaluated classifiers

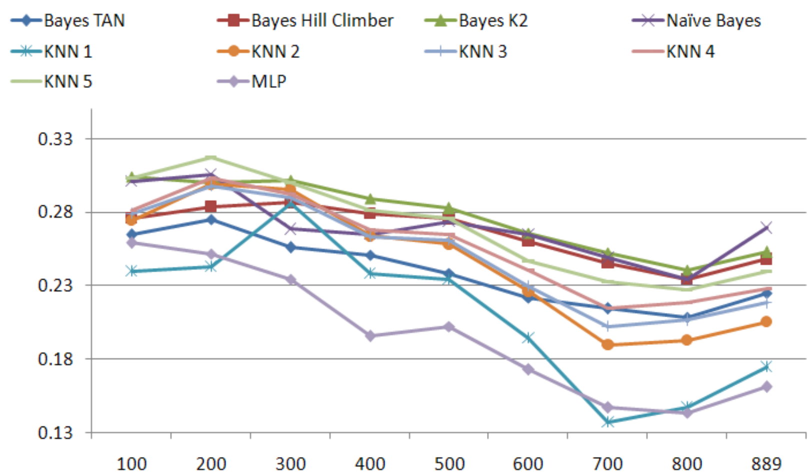

Figure 8. Mean absolute error of the evaluated classifiers

tested. Second, Bayesian networks do achieve overall good results, specifically, Bayesian networks trained with TAN perform as expected and the results were similar to the ones obtained in [44]. Finally, *MLP* outperformed the rest of the classifiers, showing that can be a interesting classifier for predicting the values of the mechanical properties.

Furthermore, Figure 8 shows the Mean Absolute Error and Figure 9 shows the Root Mean Square Error. Thereby, the results obtained are similar to the ones of prediction accuracy and MLP also outperformed the rest of algorithms in terms of error.

In addition, the classifiers have interesting results and can be used in a high-precision foundry. Remarkably, the outstanding results achieved by Multilayer Perceptron show that it can be used in a similar way as we have used the Bayesian networks in a previous work [44].

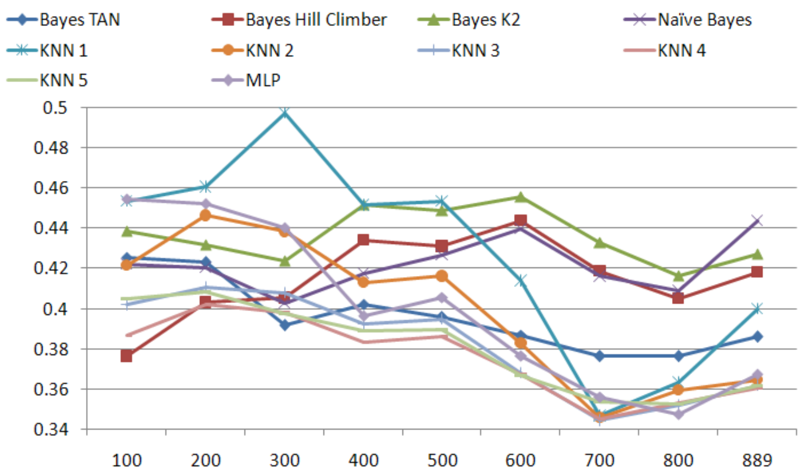

Figure 9. Root mean square error of the evaluated classifiers

7. Conclusions

On one hand, microshrinkages are tiny porosities that appear when the casting is cooling down. On the other hand, ultimate tensile strength is the capacity of a metal to resist deformation when subject to a certain load. Predicting the apparition of microshrinkages and the value of ultimate tensile strength render as the hardest issues in foundry production, due to many different circumstances and variables that are involved in the casting process and determine it.

Our work in [50] pioneers the application of Artificial Intelligence to the prediction of microshrinkages. Likewise, regarding ultimate tensile strength we presented a model to the prediction of mechanical properties [44].

To this extent, we focus here on comparing *machine-learning* classifiers used for the prediction of ultimate tensile strength and microshrinkage apparition. Specifically, we have included and adapted to our particular problem domain three classifiers that have a widely use in similar issues. All of them behave well, but Bayesian networks performed the best in the microshrinkage experiment whilst artificial neural networks outperformed the rest of the classifiers regarding ultimate tensile strength. Still, the ability of Bayesian theory and specifically, the sensitivity module cannot be ignored, since it is an effective method that provides a decision support system for the operators in the foundry plant. Therefore, with the combination of the sensitivity module and the best classifiers 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.

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 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. Finally, we plan to integrate the best classifiers in meta-classifier combining the partial results.

References

[1] J. Sertucha, A. Loizaga, and R. Suárez. Improvement opportunities for simulation tools. In *Proceedings of the 16th European Conference and Exhibition on Digital Simulation for Virtual Engineering*, 2006. invited talk.

[2] A. Zabala, R. Suárez, and J Izaga. Iron castings, advanced prediction tools, foundry process control and knowledge management. In *Proceedings of the 68*^{t}*h WFC - World Foundry Congress*, page 355360, 2008.

[3] R. Siclari, T. Margaria, E. Berthelet, and J. Fourmann. Microshrinkage in ductile iron mechanism and solution. In *Proceedings of the Keith Millis Symposium on Ductile Cast Iron*, pages 355–360, 2003.

[4] Christopher M. Bishop. *Neural Networks for Pattern Recognition*. Oxford University Press, 1995.

[5] J. Pearl. Reverend bayes on inference engines: a distributed hierarchical approach. In *Proceedings of the National Conference on Artificial Intelligence*, pages 133–136, 1982.

[6] E. Fix and J. L. Hodges. Discriminatory analysis: Nonparametric discrimination: Small sample performance. *Technical Report Project 21-49-004, Report Number 11*, 1952.

[7] S.A. Elfayoumy, Y. Yang, and S.P.: Ahuja. Anti-spam filtering using neural networks. In *Proceedings of the International Conference on Artificial Intelligence*, volume 4, pages 984–989. IC-AI.

[8] C. Zhang, J. Jiang, and M. Kamel. Intrusion detection using hierarchical neural networks. *Pattern Recognition Letters*, 26(6):779–791, 2005.

[9] Silvio Simani and Cesare Fantuzzi. Neural networks for fault diagnosis and identification of industrial processes. In *Proceedings of 10*th *Eurorean Symposium on Artificial Neural Networks (ESANN)*, pages 489–494, 2002.

[10] Zhen Yang, Xiangfei Nie, Weiran Xu, and Jun Guo. An approach to spam detection by naive Bayes ensemble based on decision induction. In *Proceedings of the Sixth International Conference on Intelligent Systems Design and Applications (ISDA'06)*, pages 861–866. IEEE Computer Society, 2006.

[11] N. A. Masruroh and K. L. Poh. A Bayesian network approach to job-shop rescheduling. In *Proceedings of the IEEE International Conference on Industrial Engineering and Engineering Management*, pages 1098–1102, 2007.

[12] Y. Liu and Shi-Qi Li. Decision support for maintenance management using Bayesian networks. In *Proceedings of the International Conference on Wireless Communications, Networking and Mobile Computing (WiCom 2007)*, pages 5713–5716, 2007.

[13] Bruce Abramson, John Brown, Ward Edwards, Allan Murphy, and Robert L. Winkler. Hailfinder: A Bayesian system for forecasting severe weather. *International Journal of Forecasting*, 12(1):57–71, 1996.

[14] A. S. Cofiño, R. Cano, C. Sordo, and J. M. Gutiérrez. Bayesian networks for probabilistic weather prediction. In *Proceedings of the European Conference on Artificial Intelligence (ECAI)*, pages 695–699, 2002.

[15] Christopher Krügel, Darren Mutz, William K. Robertson, and Fredrik Valeur. Bayesian event classification for intrusion detection. In *Proceedings of the* 19^{th} *Annual Computer Security Applications Conference*, pages 14–23, 2003.

[16] A. Faour, P. Leray, and B Eter. A SOM and Bayesian network architecture for alert filtering in network intrusion detection systems. In *Proceedings of the International Conference on Information and Communication Technologies*, pages 3175–3180, 2006.

[17] G.A. Davis and J. Pei. Bayesian networks and traffic accident reconstruction. In *Proceedings of the* 9^{th} *international conference on Artificial intelligence and law (ICAIL)*, pages 171–176, 2003.

[18] G.A. Davis. Bayesian networks, falsification, and belief revision in accident reconstruction. In *Proceedings of the Transportation Research Board* 85^{th} *Annual Meeting*, 2006.

[19] H. Zhang, A. Berg, M. Maire, and J. Malik. Svm-knn: Discriminative nearest neighbor classification for visual category recognition. In *Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR)*, volume 2, pages 2126–2136, 2006.

[20] M. Sharif and D.H. Burn. Improved k-nearest neighbor weather generating model. *Journal of Hydrologic Engineering*, 12:42, 2007.

[21] Igor Santos, Yoseba K. Penya, Jaime Devesa, and Pablo G. Bringas. N-grams-based file signatures for malware detection. In *Proceedings of the 11^{th} International Conference on Enterprise Information Systems (ICEIS), Volume AIDSS*, pages 317–320, 2009.

[22] Z.M. Lu and H. Burkhardt. Fast Image Retrieval Based on Equal-average Equal-variance K-Nearest Neighbour Search. In *Proceedings of 18^{th} International Conference on Pattern Recognition*, volume 2.

[23] J.M. Vitek, S.A. David, and C.R. Hinman. Improved ferrite number prediction model that accounts for cooling rate effects part 1 model development. *Welding Journal*, 82(10).

[24] H.Q. Peter and J. Wang. Fault detection using the k-nearest neighbor rule for semiconductor manufacturing processes. *IEEE Transactions on Semiconductor Manufacturing*, 20(4).

[25] A. Lazaro, I. Serrano, J.P. Oria, and C. de Miguel. Ultrasonic sensing classification of foundry pieces applying neuralnetworks. In *5^{t}h International Workshop on Advanced Motion Control*, pages 653–658, 1998.

[26] Pei Zhang, Zhiqiang Xu, and Fengshan Du. Optimizing casting parameters of ingot based on neural network and genetic algorithm. In *ICNC '08: Proceedings of the 2008 Fourth International Conference on Natural Computation*, pages 545–548, Washington, DC, USA, 2008. IEEE Computer Society.

[27] M. Perzyk and A. Kochanski. Detection of causes of casting defects assisted by artificial neural networks. In *Proceedings of the Institution of Mechanical Engineers Part B Journal of Engineering Manufacture*, volume 217, pages 1279–1284, 2003.

[28] H. Bhadeshia. Neural networks in materials science. *ISIJ international*, 39(10):966–979, 1999.

[29] M. Vasudevan, M. Muruganath, and A. K. Bhaduri. Application of bayesian neural network for modelling and prediction of ferrite number in austenitic stainless steel welds. *ser. Mathematical Modelling of Weld Phenomena - VI. London: Institute of Materials*, pages 1079–1100, 2002.

[30] K.D. Schnelle and R.S.H. Mah. Product quality management using a real-time expert system. *ISIJ International*, 34(10):815–821, 1994.

[31] Inoculation alloy against microshrinkage cracking for treating cast iron castings. Patent US 2005/0180876 A 1.

[32] P. Larrañaga, J. Sertucha, and R. Suárez. Análisis del proceso de solidificación en fundiciones grafíticas esferoidales. *Revista de Metalurgia*, 42(2):244–255, 2006.

[33] J. Sertucha, R. Suárez, J. Legazpi, and P. Gacetabeitia. Influence of moulding conditions and mould characteristics on the contraction defects appearance in ductile iron castings. *Revista de Metalurgia*, 43(3):188–195, 2007.

[34] J.F. Carrasquilla and R. Ríos. A fracture mechanics study of nodular iron. *Revista de Metalurgia*, 35(5):279–291, March–April 1999.

[35] R. Gonzaga-Cinco and J. Fernández-Carrasquilla. Mechanical properties dependency on chemical composition of spheroidal graphite cast iron. *Revista de Metalurgia*, 42:91–102, March–April 2006.

[36] M. Hecht and F. Condet. Shape of graphite and usual tensile properties of sg cast iron: Part 1. *Fonderie, Fondeur d'aujourd'hui*, 212:14–28, 2002.

[37] C. W. Lung and Norman H. March. *Mechanical Properties of Metals: Atomistic and Fractal Continuum Approaches*. World Scientific Pub Co Inc, 1992.

[38] American Society for Testing and Materials. ASTM D1062 - Standard Test Method for Cleavage Strength of Metal-to-Metal Adhesive Bonds, 2008.

[39] American Society for Testing and Materials. ASTM B489 - e1 Standard Practice for Bend Test for Ductility of Electrodeposited and Autocatalytically Deposited Metal Coatings on Metals, 2008.

[40] T. Bayes. An essay towards solving a problem in the doctrine of chances. *Philosophical Transactions of the Royal Society*, 53:370–418, 1763.

[41] Enrique Castillo, José M. Gutiérrez, and Ali S. Hadi. *Expert Systems and Probabilistic Network Models*. Springer, New York, NY, USA, erste edition, December 1996.

[42] J. Pearl and S. Russell. Bayesian networks. Technical Report Tech. Rep. R-216, Computer Science Department, University of California, Los Angeles, 2000.

[43] Chan K. Saltelli, A. and and Scott E. M. *Sensitivity Analysis: Gauging the Worth of Scientific Models*. Springer, New York, NY, USA, wiley edition, August 2000.

[44] Javier Nieves, Igor Santos, Yoseba K. Penya, Sendoa Rojas, Mikel Salazar, and Pablo G. Bringas. Mechanical properties prediction in high-precision foundry production.

[45] Donald Michie, D. J. Spiegelhalter, C. C. Taylor, and John Campbell, editors. *Machine learning, neural and statistical classification*. Ellis Horwood, Upper Saddle River, NJ, USA, 1994.

[46] R. Kohavi. A study of cross-validation and bootstrap for accuracy estimation and model selection. In *International Joint Conference on Artificial Intelligence*, volume 14, pages 1137–1145, 1995.

[47] Gregory F. Cooper and Edward Herskovits. A bayesian method for constructing bayesian belief networks from databases. In *Proceedings of the 7th conference on Uncertainty in artificial intelligence*, 1991.

[48] S. J. Russell and Norvig. *Artificial Intelligence: A Modern Approach (Second Edition)*. Prentice Hall, 2003.

[49] Dan Geiger, Moises Goldszmidt, G. Provan, P. Langley, and P. Smyth. Bayesian network classifiers. In *Machine Learning*, pages 131–163, 1997.

[50] Y.K. Penya, P. García Bringas, and A. , Zabala. Advanced fault prediction in high-precision foundry production. In *Proceedings of the* 6th *IEEE International Conference on Industrial Informatics*, pages 1673–1677, 2008.

[51] C.G. Thomas, R.A. Harshman, and R.S. Menon. Noise reduction in BOLD-based fMRI using component analysis. *Neuroimage*, 17(3):1521–1537, 2002.