Supervised Learning Classification for Dross Prediction in Ductile Iron Casting Production

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***Abstract*—Foundry is one of the key axes in society because it provides with important pieces to other industries. However, several defects may appear in castings. In particular, Dross is defect that is a type of non-metallic, elongated and filamentary inclusion. Unfortunately, the methods to detect Dross have to be performed once the production has already finished using quality controls that incur in a subsequent cost increment. Given this context, we propose the first machine-learning-based method able to foresee Dross in iron castings, modelling the foundry production parameters as input. Our results have shown that this method obtains good accuracy results when tested with real data from a heavy-section casting foundry.**

I. Introduction

Spheroidal graphite irons (SGI) or ductile irons were developed and patented for the International Nickel Company Research Laboratory by Keith Millis et al. in the 1940s [1]. After more than sixty years of development, SGI have become an economically interesting group of materials with interesting physical properties as high toughness, corrosion resistance or high tensile strength [2] and applications in automotive, wind mills or tooling industries. These properties are due to the different microstructures which are available both in the as-cast or heat-treated states.

One of the main structural characteristic of cast irons is the shape of graphite particles which are present in the metallic matrix. In SGI, graphite is formed as spherical particles or nodules rather than flakes as in lamellar graphite irons (also named grey irons). The spherical growth of nodules is promoted by the addition of nodularizing elements such as Mg or Ce [2], [3] to melts usually by means of FeSiMg or Misch-Metal alloys.

The technological and economic advantages of SGI have increased the production of this type of alloy during the last sixty years up to a world production of 23 Mt per year in 2010 [4]. Approximately 2 Mt per year are produced for heavy-section castings meanwhile 0.5 Mt are used to manufacture cast parts for the wind mills industry [5]. This strong development has also required important advances in both processing knowledge and control in order to produce sound cast parts with complex geometries and satisfactory mechanical properties.

In the case of heavy-section castings produced for wind mills, customer requirements and competence have increased rapidly. As a consequence of this, parameters like the surface quality or the appearance of internal inclusions become critical aspects when validating the functionality of the cast parts. It has been reported in the literature [6], [7] that both, surface defects and sand/slag inclusions, negatively affect the fatigue behaviour by acting as stress raiser spots that promote crack initiation during the service period. Thus one of the most important challenges of heavy-casting foundries is to manufacture as-cast parts free of sand or slag inclusions, with high surface quality and also with lower costs.

Amongst the various types of slag inclusions, Dross and Dross-pitting are the most representative and detrimental. Specifically, Dross is a non-metallic inclusion with elongated and filamentary aspect [6] usually surrounded by degenerated graphite (lamellar and/or vermicular shapes). In contrast to sand inclusions, the origin of Dross particles is endogenous and it is associated with the high reactivity of Oxygen, Silicon and Magnesium, this last added during the necessary spheroidization treatment. Several technical papers [6], [8]–[10] have been published for describing the characteristics of this defect and for determining the mechanisms and factors that have influence on Dross appearance. The results of these works are useful to implement some general rules when manufacturing heavy-section cast parts. However, this understanding is not still enough to optimise the production processes and to obtain the minimum rejection levels.

An effective combination of machine-learning tools and the available processing data coming from foundries must lead to a deeper understanding about how the processing parameters and cast parts characteristics affect Dross formation.

Besides, a prediction tool for this parameter would lead foundries to lower reject rates and the subsequent cost and time saving. Successful machine-learning approaches related with other foundry problems have been previously reported in [11]–[18].

Against this background, we present here the first machine learning based tool that has been developed and, then, successfully applied to predict and to prevent Dross defects in cast iron parts. The data base used contained experimental processing parameters and defect evaluation on parts as output data.

In summary, our main contributions are:

- We study the variables to represent the Dross formation as a machine learning classification task.
- We adapt the machine-learning algorithms for the Dross

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prediction.

- We show that our method is capable of predicting Dross with a high accuracy.

The remainder of this paper is organised as follows: Section II details the casting production process. Section III describes the problem of Dross formation. Section IV describes the different method that we have applied to this particular problem domain. Section V describes the experiments and presents results. Finally, Section VI concludes the paper and outlines avenues for future work.

II. Manufacture of Heavy-section Cast Parts

Cast iron foundries are companies that produce a wide range of different cast parts which complex designs and close to their final shape. Basically, these castings are manufactured by pouring molten alloys in sand moulds after controlling the chemical composition and the quality of melts. Before pouring, moulds must be prepared placing the needed cores to create internal sections. Once metal is cooled sufficiently ($200 - 500°\mathrm{C}$) the casting is removed from the sand and then properly cleaned and finished. Figure 1 details the manufacturing process for the production for heavy-section parts.

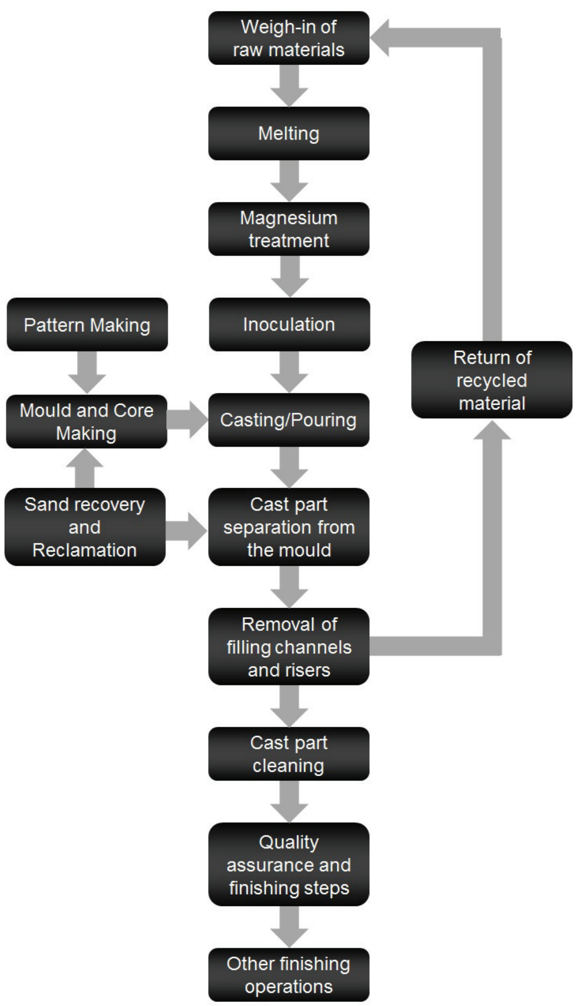

Fig. 1. Different steps in heavy-section castings production.

A. Pattern making and Mould Design

Moulding and core-making patterns respectively provide the exterior and interior shape of any designed heavy-section casting. These patterns are normally produced in wood or polystyrene (this last also called as 'lost foam moulding'). In this step, simulation tools are essential to design the filling systems and to evaluate the needs of risers in the final layouts. These last feeders are used to avoid the formation of shrinkage defects during solidification.

B. Mould-making and Core-making

Production of heavy-section castings requires big moulds which are normally manufactured using chemical-bonded sand mixtures. For this purpose, controlled mixtures composed by recycled sand, new sand, furanic resins and acid catalysts are prepared using continuous mixers in plants. The prepared sand mixtures are rapidly added on framed patterns and hand-squeezed before sand hardening. After several hours, the mould components are removed from patterns, cores are then inserted and finally moulds are finished by assembling the different components. The current preparation of moulds for heavy-section castings is still a quite handmade process. Mould and core physical properties are usually controlled by means of several standardized analysis made both on the produced sand mixtures and on the materials used to prepare them.

C. Weigh-in of Raw Materials

Chemical features of the final castings mainly depend on the composition of the metallic charges added to the melting furnace and on the type of raw materials employed (low alloyed pig iron, internal returns and steel scrap among others). Both aspects strongly depend on market conditions, thus, foundries have to take into account the existing prices and availability of raw materials, and the casting requirements when managing the needed melts composition.

D. Melting

Designed metallic charges are gradually introduced in a melting furnace (usually a medium frequency induction furnace though cupolas, electric arc furnaces or rotary furnaces are also utilized). After melting, chemical composition of molten alloys is checked and adjustments are normally required by means of the addition of specific Fe-alloys or alloying elements. Then the liquid metal temperature is increased to $1400 - 1450°\mathrm{C}$ and its surface properly skimmed. In this step, the obtained melt composition, called as 'base metal', is checked again by spectrometry, combustion techniques and/or thermal analysis.

E. Magnesium Treatment

Spherical shape of graphite particles precipitated in ductile cast irons becomes the cause of their interesting mechanical properties. In particular, ferritic ductile irons with impact and fatigue requirements for wind mill industry strongly depend on the correct shape of graphite nodules and on nodule count. The active element to achieve the desirable graphite particles shape is Magnesium (called as 'nodularising agent').

This chemical element is normally added via a FeSiMg master-alloy which is added to the base metal. A nodularising ladle is used for this purpose. Before transferring the base metal from the melting furnace, the FeSiMg alloy is placed in a reaction chamber located in the bottom of the nodularising ladle. Then the FeSiMg is covered (usually adding steel scrap returns from stamping processes) to delay the start of the reaction between the transferring base metal and the master-alloy. When the reaction is accomplished, the resulting batch surface is skimmed and its temperature and chemical composition measured. In modern heavy-section foundry plants, the quality of the prepared melts is measured by Thermal Analysis techniques in order to evaluate, among others, its graphite nucleation potential. Finally, the Mg-treated melt is transferred to the corresponding pouring area.

F. Inoculation

In addition to Magnesium, an effective inoculation process is needed to guarantee the suitable spherical shape of precipitated graphite particles. Additionally, inoculation is also essential to obtain high nodule counts (homogeneous distribution of graphite nodules in the metallic matrix). Inoculation consists in the addition of a controlled amount of an inoculant product to the melt just before pouring the mould. Inoculants are normally composed by a FeSi alloy that contains other active elements (Ca, Al, Sr, Zr, etc.) to promote graphite nucleation and growth during solidification of cast irons.

It is usual to find two different inoculation steps in heavy-section castings production. An early inoculation (also called as ‘pre-inoculation’) is performed in the nodularising ladle adding the inoculant in the reaction chamber on the FeSiMg master-alloy. On the other hand, a post-inoculation is carried out when pouring the mould by placing some inoculant blocks in the gating system.

G. Casting or Pouring Process

Before starting the mould filling, the Mg-treated and inoculated melt is usually placed in a basin located in the top of the mould. It is critical to keep under control variables as the melt temperature and the filling time.

H. Cast Part Separation from the Mould (Shake-out)

After cooling, the cast part must be removed from the mould by shaking the casting-mould system in a grid. This procedure extracts the major amount of sand from the cast part, filling channels and feeders. Cooling rate has an important influence on microstructural characteristics and on mechanical properties of cast irons. Thus, cast parts have to remain in the mould until the required temperature so as to guarantee that the obtained microstructure is correct. For ferritic heavy-section castings, the maximum temperature in the part must be lower than 600°C before removing it from the mould. Hence, the time between pouring the mould and removing the cast part takes several days depending on the weight of metal poured in the mould.

I. Removal of Filling Channels and Risers

Once the casting is extracted from the mould, filling channels and feeding systems (these last tools are used to compensate for the lack of mass due to the contraction of melts during solidification and, consequently, to minimise the formation of shrinkages) are separated from the cast part. They are regularly removed by knocking off, sawing or cutting.

J. Cast Part Cleaning

The objective of this step is to remove the residual sand still stuck to the cast part surface by shot-blasting. This procedure consists in rapidly impacting the surface of the part with a controlled stream of abrasive metallic shots. This step allows cleaning the part surface for subsequent inspections.

K. Quality Assurance and Finishing Step

Once the cast part surface has been correctly cleaned, a number of controls have to be made to determine the validity of it according to the established customer requirement. These controls depend on the casting type and its application. The ferritic heavy-section cast parts produced for wind mills are object of intensive evaluation controls. These parts are used for applications that demand important fatigue efforts. So any shrinkage, Dross inclusion, gas porosity and/or sand inclusion that are present in the metallic matrix have a negative effect on this critical demand. Therefore, the potential presence of any of these defects is exhaustively controlled for each cast part according to the specifications established by the customers or end-users. The appearance of any of the defects mentioned above will require additional cleaning operations to eliminate all affected areas and to fulfil the customer requirements. This additional cleaning works strongly increase the costs linked to the manufacture of each cast part. When the importance of the defects consequences is big enough, the cast part will be rejected with important costs for the foundry. The usual required controls for ferritic cast parts produce for wind mills are the following:

- Visual inspection of all surfaces to detect external defects (inclusions, high roughness, geometric problems, blow holes, etc.).
- Magnetic particles inspection for a detailed detection of surface defects. The detected defects have to be removed by wearing down all affected areas.
- Ultrasound inspection to detect and evaluate internal defects (shrinkages, Dross inclusions, sand inclusions, gas porosities, etc.). The detected defects have to be eliminated by wearing down all affected areas.
- Second visual inspection after removing the possible areas with defects and then after shot-blasting again the cast part.
- Chemical analysis of the melt poured into the mould.
- Complete metallographic analysis on the demanded casting areas and/or samples.
- Mechanical properties measurement on the demanded casting areas and/or samples. Tensile strength, yield strength, elongation and impact properties at different

temperatures are typically controlled in ferritic heavy-section castings produced for wind mills.

L. Other Finishing Operations

After finishing and validating a cast part, other finishing operations are required (machining, painting, application of corrosion preventive coating, etc.). Although these subsequent finishing operations are not directly linked to the foundry process, some of the most modern foundries include them among their activities in order to offer their clients a product with an increased added value. It is necessary to emphasize here that machining processes may discover internal defects on castings that were not detected in previous control tests. Such results would complicate the final validation of the involved cast part.

III. Dross inclusions and Affecting Variables

Slag inclusions are one of the most common defects found in ductile iron parts. These inclusions are oxides that are formed by the reaction of different chemical elements involved in the nodularisation and inoculation treatments. The term 'Dross' is normally referred to an internal slag inclusion (Figure 2) with elongated and filamentary aspect and usually surrounded by degenerated graphite particles. Although the composition of Dross inclusions can be more complex, MgO and SiO^2 oxides are normally found when analysing them.

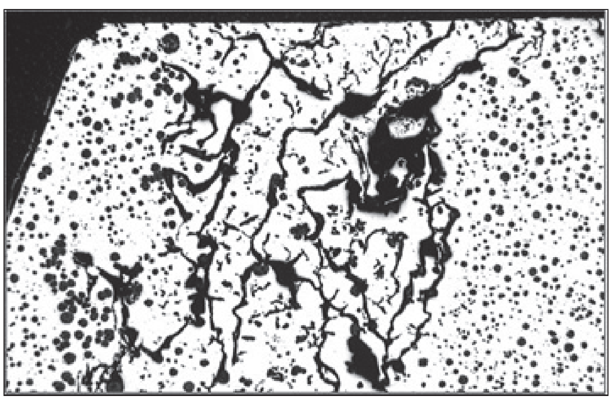

Fig. 2. Dross defect in a ductile iron part.

The presence of slag inclusions is frequently linked to problems when cleaning the Magnesium treated melts before pouring. However, Dross defect can be detected in cast parts even when using correctly skimmed melts. This fact is a consequence of the continuous formation of Dross in the internal mass of liquid irons before solidifying. In such condition, active elements as Si and Mg progressively react and oxides and other complex compounds are precipitated. Therefore, the resulting inclusions occupy small internal areas of the solid material and an important negative effect on its mechanical properties will be obtained. Three different main causes are considered in foundry plants regarding Dross inclusions: chemical composition of melt, turbulences when filling the moulds and pouring temperatures. However a proper control of these factors does not seem to be enough to minimize the appearance of this defect and other processing variables must be taken into account.

IV. Machine Learning Techniques

Machine-learning is an active research area within *Artificial Intelligence* (AI) that focuses on the design and development of new algorithms that allow computers to reason and decide based on data [19].

Machine-learning algorithms can commonly be divided into three different types depending on the training data: supervised learning, unsupervised learning and semi-supervised learning. For supervised algorithms, the training dataset must be labelled (e.g., the defect in the casting) [20]. Unsupervised learning algorithms try to determine how data are organised into different groups named clusters. Therefore, data do not need to be labelled [21]. Finally, semi-supervised machine-learning algorithms use a mixture of both labelled and unlabelled data in order to build models, improving the accuracy of solely unsupervised methods [22].

Because castings can be properly labelled, we use supervised machine-learning; however, in the future, we would also like to test unsupervised methods for automatic categorisation of foundry defects.

A. Bayesian Networks

Bayesian Networks [23], which are based on the *Bayes Theorem*, are defined as graphical probabilistic models for multivariate analysis. Specifically, they are directed acyclic graphs that have an associated probability distribution function [24]. Nodes within the directed graph represent problem variables (they can be either a premise or a conclusion) and the edges represent conditional dependencies between such variables. Moreover, the probability function illustrates the strength of these relationships in the graph [24].

The most important capability of Bayesian Networks is their ability to determine the probability that a certain hypothesis is true (e.g., the probability of a casting to have certain defect) given a historical dataset.

B. Decision Trees

Decision Tree classifiers are a type of machine-learning classifiers that are graphically represented as trees. Internal nodes represent conditions regarding the variables of a problem, whereas final nodes or leaves represent the ultimate decision of the algorithm [25].

Different training methods are typically used for learning the graph structure of these models from a labelled dataset. We use *Random Forest*, an ensemble (i.e., combination of weak classifiers) of different randomly-built decision trees [26], and *J48*, the WEKA [27] implementation of the *C4.5* algorithm [28].

C. K-Nearest Neighbour

The *K-Nearest Neighbour* (KNN) [29] classifier is one of the simplest supervised machine learning models. This method classifies an unknown specimen based on the class of the instances closest to it in the training space by measuring the distance between the training instances and the unknown instance.

Even though several methods to choose the class of the unknown sample exist, the most common technique is to simply classify the unknown instance as the most common class amongst the K-nearest neighbours.

D. Support Vector Machines (SVM)

SVM algorithms divide the n-dimensional space representation of the data into two regions using a *hyperplane*. This hyperplane always maximises the *margin* between those two regions or classes. The margin is defined by the farthest distance between the examples of the two classes and computed based on the distance between the closest instances of both classes, which are called *supporting vectors* [30].

Instead of using linear hyperplanes, it is common to use the so-called *kernel functions*. These kernel functions lead to non-linear classification surfaces, such as polynomial, radial or sigmoid surfaces [31].

V. Empirical Validation

The acceptance/rejection criterion of the studied models resembles the one applied by the final requirements of the customer. Cast parts flawed with defects must be rejected due to the very restrictive quality standards (which is an imposed practice by the automotive industry). To this end, we labelled each possible segment within the castings with its defects.

A whole dataset that contained records from the most important processing variables involved in a heavy-section casting foundry process was created. 120 different parameters related with raw materials, chemical composition of melt, thermal analysis data, inoculation, magnesium treatment, pouring time and pouring temperature, etc. were collected in addition to the output data. In this last case, the volume affected by Dross measured by ultrasound inspection on each produced cast part was selected as output variable.

Next, we evaluate the precision of the machine-learning method to predict the value of Dross. The final level of Dross was discretized in 5 different categories in order to apply classification techniques:

1) $Dross \leq 2.5$
2) $2.5 < Dross \leq 3.5$
3) $3.5 < Dross \leq 4.5$
4) $4.5 < Dross \leq 5.5$
5) $5.5 < Dross \leq 6.5$
6) $Dross > 6.5$

Hereafter, by means of the dataset, we conducted the following methodology to evaluate the proposed method:

- **Cross validation:** This method is generally applied in machine-learning evaluation [32]. In our experiments, we performed a K-fold cross validation with $k = 10$. In this way, our dataset is 10 times split into 10 different sets of learning (90 % of the total dataset) and testing (10 % of the total data).
- **Learning the model:** For each fold, we accomplished the learning step of each algorithm using different parameters for the learning algorithms depending on the specific model. In particular, we used the following models:
  – *Bayesian networks (BN):* With regards to Bayesian networks, we utilize different structural learning algorithms: K2 [33] and Tree Augmented Naïve (TAN) [34]. Moreover, we also performed experiments with a Naïve Bayes Classifier [32].
  – *Support Vector Machines (SVM):* We performed experiments with a polynomial kernel [31], a normalised polynomial Kernel [35], a Pearson VII function-based universal kernel [36] and a radial basis function (RBF) based kernel [37].
  – *K-nearest neighbour (KNN):* We performed experiments with $k = 1$, $k = 2$, $k = 3$, $k = 4$, and $k = 5$.
  – *Decision Trees (DT):* We performed experiments with J48(the *Weka* [27] implementation of the *C4.5* algorithm [28]) and Random Forest [26], an ensemble of randomly constructed decision trees. In particular, we tested random forest with a variable number of random trees N, $N = 10$, $N = 20$, $N = 30$, $N = 40$, and $N = 50$.
- **Testing the model:** To test the approach, we evaluated the percent of correctly classified instances and the area under the ROC curve (AUC), which establishes the relation between false negatives and false positives [38].

TABLE I
Results of Dross Prediction in terms of Accuracy and Area Under the ROC Curve (AUC).

Classifier	Accuracy(%)	AUC
Naïve Bayes	47.86±3.06	0.7690±0.05
BN: K2	62.63±2.94	0.8939±0.03
BN: TAN	74.92±2.81	0.9560±0.02
KNN K = 1	30.20±2.89	0.5888±0.05
KNN K = 2	30.67±2.78	0.6323±0.05
KNN K = 3	30.25±2.93	0.6602±0.05
KNN K = 4	31.22±2.89	0.6672±0.05
KNN K = 5	30.99±2.82	0.6753±0.05
SVM: Polynomial Kernel	57.07±2.76	0.8135±0.04
SVM: Normalised Polynomial Kernel	50.92±3.08	0.7779±0.04
SVM: RBF Kernel	44.78±2.79	0.7165±0.04
SVM: Pearson VII Kernel	62.59±2.72	0.8239±0.04
DT: J48	62.97±3.23	0.8157±0.06
DT: RandomForest N = 10	70.23±3.00	0.8999±0.03
DT: RandomForest N = 20	72.54±2.55	0.9223±0.02
DT: RandomForest N = 30	73.33±2.56	0.9296±0.02
DT: RandomForest N = 40	73.65±2.39	0.9334±0.02
DT: RandomForest N = 50	73.87±2.31	0.9356±0.02

Table I shows the obtained results for Dross prediction in terms of accuracy and area under the ROC curve. In this way, the best results were obtained by Bayesian Networks trained with Tree Augmented Naïve, with a 74.92% of accuracy and a 0.9560 of AUC. Random Forest classifiers also obtained good results with accuracy values higher that 70% and AUCs higher than 0.89. Instance-based classifiers were the worst classifiers with very poor results.

The results show that this method can be used in a high-precision foundry. Remarkably, the good results achieved by the Bayesian network trained with Tree Augmented Naïve show that it can be used in a similar way as we have used the Bayesian networks in previous works, for this defect. In this way, combining the better classifiers and using them for the defects that suit best, we can reduce the cost and the duration of the actual testing methods, and provide an effective quality control method.

Our experience shows that the behaviour of the system can be deployed in the following way: when the system detects that the probability of a inappropriate value of Dross 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. Conclusions and Future Work

In this paper, we have presented a novel supervised learning based approach for Dross defect detection in iron castings. This method achieves good results in terms of accuracy.

Future work will be focused on three main directions. First, we will utilise different features and methods for training these kinds of models. Second, we will extend our study of supervised learning by applying more algorithms to this issue. Finally, we are going to focus on different defects in foundry production in order to generate a general fault detector.

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