Serbian Tribology Society

SERBIATRIB '19

16th International Conference on Tribology

Faculty of Engineering
University of Kragujevac

Kragujevac, Serbia, 15 – 17 May 2019

EVALUATION OF HARDNESS IN CAST IRON: HOW SIMPLE IT IS !

Cristiano FRAGASSA[1,*], Matej BABIC[2], Ana PAVLOVIC[1]

[1] Department of Industrial Engineering, University of Bologna, Bologna, Italy

[2] Jožef Stefan Institute, Ljubljana, Slovenia

*Corresponding author: cristiano.fragassa@unibo.it

Abstract: *The accurate prediction of the mechanical properties of foundry alloys is a rather complex charge given the substantial variability of metallurgical conditions that can be created during casting even in the presence of minimal variations in the constituents and in the process parameters. In this study an application of intelligent methods, based on the machine learning, to the estimation of the hardness of a traditional spheroidal cast iron and a less common compact graphite cast iron is proposed. Microstructures are used as inputs to train the neural networks, while hardness is obtained as outputs. As general result, it is possible to admit that 'light' open source self-learning algorithms, combined with databases consisting of about 20-30 measures are already able to predict hardness properties with errors below 15%.*

Keywords: *Hardness prediction, Artificial Intelligence (AI), Machine Learning (ML), nodular/spheroidal cast iron (SGI), compact graphite cast iron (CGI), foundry process.*

1. INTRODUCTION

The family of cast irons consists of a large number of alloys, each one qualified by its own characteristics in terms of metallurgic composition, mechanical properties, surface resistance, and, ultimately, practical use. Perhaps, exactly for this variability, cast iron is one of the most used materials in industrial history and in the present by mankind [1].

The first attempts at producing cast iron in the Mediterranean basin can be traced back to over 1000 BC and tower ovens were found in Sweden, dated between 1150 and 1350.

Few modifications (as additives inoculation) are sufficient to produce materials with very different characteristics and applications, from the common gray iron to the high performing ductile cast iron.

This complexity in properties estimation is even more evident in the case of superficial features as the hardness. In this case, beyond all other aspects dealing with the overall variability of material characteristics, also additional considerations related to local effects in cooling start to be predominant.

However, limiting to the industrial purposes, often it would be sufficient to have quick indications regarding these properties, even if not extremely precise. In this study intelligent methods based on machine learning (ML) are proposed to estimate the hardness of a traditional spheroidal cast iron (SGI) and of a less common compact graphite cast iron (CGI).

Microstructural macroindicators, as, e.g., the quantity of graphite, ferrite, perlite in the alloy, acquired by microstructures, are used as inputs to train three (3) different ML algorithms, while hardness properties (in HB) are obtained as outputs.

Two datasets from tests were considered, one per each material, consisting of 25-30

samples, while comparisons were done by a direct correlations with the estimations.

2. EVALUATION METHODS

Several methods of ML can be conveniently considered. In the present work, according to preceding similar experiences, as detailed in [2], the following ones were preferred.

2.1 Random Forest (RF)

The RF is one of the most popular and extremely effective methods for solving the problems of machine learning, such as classification and regression [3].

A NN is a structure (network) consisting of a set of interconnected links (artificial neurons). Each link has a characteristic input / output and implements a local calculation or function. The output of any link is determined by the characteristics of its input / output, its relationship with other links, as well as external inputs, if any.

In terms of efficiency, it competes with support vector machines, neural networks and boosting, although it certainly does not lack its shortcomings. In appearance, the learning algorithm is very simple (in comparison with the learning algorithm of the support vector machines). The basic ideas laid down in Random Forest model (binary decision tree, bootstrapping aggregation or bagging, random subspace method and decorrelation).

2.2 Neural Network (NN)

The NN also represents a quite common strategy in problem solving. A NN can be used to build an efficient encryption system using a constantly changing key. The NNs offer a very powerful and general structure for representing a non-linear mapping of several input variables for several output variables. A NN can be considered as a suitable choice for functional forms used for encryption and decryption operations.

The NN topology is an important issue, since the application of the system depends on it. Therefore, since the application is a calculation problem, a multi-layered topology was used. Then, the NNs offer a very powerful and general structure for representing a non-linear mapping of several input variables for several output variables. The process of determining the values of these parameters on the basis of a data set is referred to as training or training, and therefore the data set is usually referred to as a training set. In particular, a NN can be considered as a suitable choice for functional forms used for encryption and decryption operations.

2.3 k-nearest neighbors (kNN)

The kNN is a non-parametric method used for classification and regression [5]. The input consists of the k closest training examples in the feature space. The output depends on whether k-NN is used for classification or regression.

In k-NN classification, the output is a class membership. An object is classified by a plurality vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbor. In k-NN regression, the output is the property value for the object. This value is the average of the values of its k nearest neighbors. The k-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. The k-NN algorithm is among the simplest of all machine learning algorithms. Both for classification and regression, a useful technique can be used to assign weight to the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbor a weight of 1/d, where d is the distance to the neighbor.

The neighbors are taken from a set of objects for which the class (for k-NN classification) or the object property value (for

k-NN regression) is known. This can be thought of as the training set for the algorithm, though no explicit training step is required. A peculiarity of the k-NN algorithm is that it is sensitive to the local structure of the data.

3. DATA ESTIMATIONS

Measures used in this investigation for training the ANNs derived from mechanical and tribological tests already discussed in details in previous works [6-8]. In particular, in accordance with [8] the datasets consist of 27 samples in SGI and 21 samples in CGI.

As input for training the ANN, the following metallographic parameters were chosen:

- Graphite
- Ferrite
- Perlite
- Grade of nodularity
- Grade of vermicularity

These data were provided in terms of single values estimated by micrographs: each sample (SGI and CGI) provided a specific set of 5 (five) values. Every set (21+27) of metallographic characteristics was combined with the related hardness property as measure by test.

ANN evaluations were implemented by Orange algorithms, an open source machine learning and data visualization system [9]. The ANN was learned by these data and provided outputs in terms of HB hardness. In particular, per each sample, it provided 3 (three) different estimations of hardness in accordance with the 3 (three) specific methods used:

- Random Forest (RF)
- Neural Network (NN)
- k-Nearest Neighbors (kNN)

These values are reported in table 1 and 2. Table 3 reports the related values of:

- mean ($\boldsymbol{\mu}$),
- standard ($\boldsymbol{\sigma}$)
- relative standard ($\boldsymbol{\sigma_{\%}}$) deviation
- Pearson correlation coefficient ($\boldsymbol{\rho_{xy}}$)

In the way to show the overall variability of values and permit a comparison of methods.

Table 1. SGI Hardness as measured and estimated

N.	HB	RF	NN	kNN
1	165	182	168	181
2	166	174	171	171
3	167	178	178	173
4	168	182	182	169
5	169	182	171	168
6	171	182	182	169
7	171	182	182	166
8	173	171	182	171
9	173	182	184	165
10	174	181	178	167
11	176	204	184	165
12	178	182	181	165
13	178	181	182	171
14	180	176	206	183
15	181	178	178	169
16	181	173	173	165
17	182	178	178	171
18	182	173	171	165
19	182	178	171	171
20	183	184	206	180
21	184	180	176	176
22	185	169	182	169
23	186	190	204	180
24	190	185	206	180
25	204	206	206	206
26	206	183	190	180
27	206	204	204	180

Table 2. CGI Hardness as measured and estimated

N.	HB	RF	NN	kNN
1	132	148	137	137
2	136	141	141	139
3	137	145	145	142
4	139	142	136	136
5	141	142	144	142
6	142	147	144	141
7	142	151	156	147
8	144	142	149	141
9	144	142	145	137
10	145	132	137	137
11	146	150	149	147
12	147	147	132	132
13	147	147	151	151
14	147	147	151	151
15	148	150	147	132
16	149	147	156	144
17	150	146	148	146
18	150	142	147	142
19	151	147	147	147
20	151	147	147	147
21	156	147	151	141

Table 3. Mean (μ), standard deviation (σ) and relative standard ($\sigma_{\%}$) deviation, and, finally, the Pearson correlation coefficient (ρ_{xy}) for SGI and CGI hardness, as measured (HB) and estimated

	HB	RF	NN	kNN	
μ	180	182	184	173	SGI
σ	11	9	12	9	
$\sigma_{\%}$	6%	5%	7%	5%	
ρ_{xy}	1.00	0.46	0.59	0.56	
μ	144	145	146	142	CGI
σ	5	4	6	5	
$\sigma_{\%}$	4%	3%	4%	3%	
ρ_{xy}	1.00	0.17	0.43	0.28	

4. RESULTS

Measures and estimations can be graphically observed and compared in Figure 1 for SGI and CGI. In particular it can be observed the estimation provided by the *NN* method that, according to the Pearson correlation coefficients (ρ_{xy}) in Table 3 can be considered the most appropriate evaluation method. In fact, with value of 0.59 and 0.43 in the case of, respectively, SGI and CGI, it demonstrates a good (even not perfect) correlation between the experimental dataset and the estimated hardness.

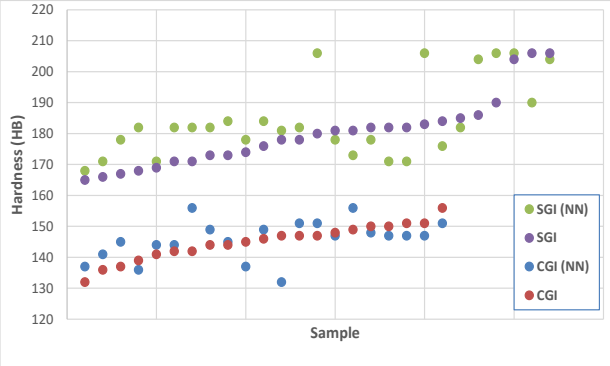

Figure 1. Measured and estimated hardness (HB) for SGI (up) and CGI (down)

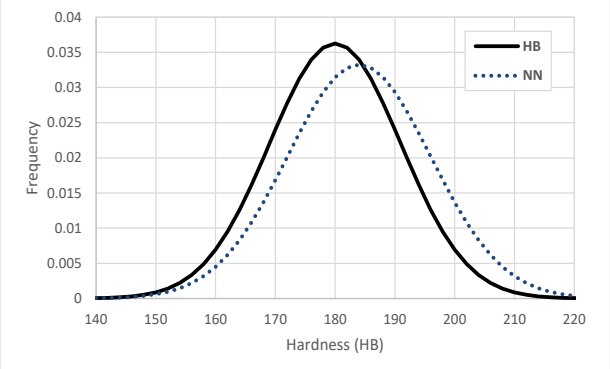

Figure 2. Overlapping between measures and estimations (in the case of SGI and NN)

This estimation by the NN method is able to guarantee a substantial coincidence on the average values of hardness (184 vs 180 in the case of SGI, 146 vs 144 for CGI) and its variability (e.g. in terms of relative standard deviations). It means that, as evident in Figure 2, there is a significant overlapping between the density distributions able to represent measures and estimations in terms of probability.

Moreover, all methods for Machine Learning under investigation seem able to provide an adequate estimation, especially when considered the real values. In Figure 3 it is shown, for instance in the case of SGI, the influence of the choice (MF, NN or kNN) in the estimation.

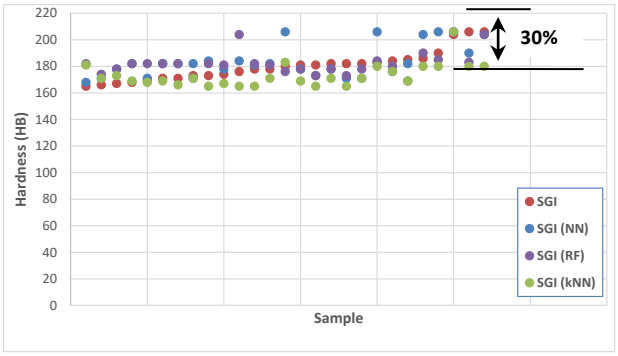

Figure 3. Comparison between the estimation methods (in the case of SGI)

In particular, in the graph it is possible to see how the variability in hardness predictions was limited within a range of 30% respect to the average measure. This result can be considered more than appropriate concerning that:

- Even if the specimens were extracted from the similar casting conditions, the experimental values were characterized by a certain intrinsic variability (σ = 11). This variability was transferred in the ANN evaluation even if with a tendency to a reduction.
- The use of ANN has not been optimized in this case, nor as structure or training. This choice is related to a specific strategy aiming at demonstrating the applicability of the ANN theory without entering in further details.

5. CONCLUSION

The present research deals with the use of Artificial Intelligence (AI) and Machine Learning (ML) in the prediction of hardness of spheroidal cast iron (SGI) and compact

graphite cast iron (SGI). Results from previous experiments were used to train three ANNs, based on three different principles. Open source and easy accessible algorithms were used. Even if in the presence of a limited number of measures (20-30), the ANNs, independently of the specific network, were able to predict the hardness with an acceptable confidence (±15%).

It is believed that a greater accuracy could be easily achieved by: i) increasing the sample of measures on which the ANN is trained; ii) optimizing the ANN in terms of depth and quality of analysis ('deep learning'), but also testing the opportunity to choose other methods of estimation (as Multiple Regression, Nearest Neighbors, Genetic Programming, Support Vector Machine…); iii) using microstructural information directly at a level of details.

ACKNOWLEDGEMENT

This research was implemented by the support of SCM Foundries, Italy, where the different samples of cast iron were produced. Special thanks to Giangiacomo Minak, Stefano Cucchetti and Giuseppe Lucisano.

REFERENCES

[1] C. Fragassa, G. Minak, A. Pavlovic: Tribological aspects of cast iron investigated via fracture toughness, Tribology in Industry, Vol. 38, No. 1, pp. 1-10, 2016.

[2] M. Babic, M. Calì, I. Nazarenko, C. Fragassa, S. Ekinovic, M. Mihaliková, M. Janjić, I. Belič: Surface Roughness Evaluation in Hardened Materials by Pattern Recognition Using Network Theory, International Journal on Interactive Design and Manufacturing, 2018.

[3] Y. Lin, J. Yongho: Random forests and adaptive nearest neighbors, Journal of the American Statistical Association, Vol. 101, No. 474, pp. 578–590, 2006.

[4] S. Jürgen: Deep learning in neural networks: An overview, Neural Networks, Vol. 61, pp. 85–117, 2015.

[5] S. Garcia, J. Derrac, J. Cano, F. Herrera: Prototype Selection for Nearest Neighbor Classification: Taxonomy and Empirical Study, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 34, No. 3, pp. 417–435, 2012.

[6] N. Radovic, A. Morri, C. Fragassa: A Study on the Tensile Behavior of Spheroidal and Compacted Graphite Cast Irons Based on Microstructural Analysis, in: *Proceeding of the 29th Danubia Adria Symposium on Experimental Solid Mechanics*, 26-29.09.2012, Belgrade, Serbia, pp. 164-170, 2012.

[7] C. Fragassa: Material selection in machine design: the change of cast iron for improving the high-quality in woodworking, *In Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, Vol 231, No. 1, pp. 18-30, 2016.

[8] C. Fragassa, N. Radovic, A. Pavlovic, G. Minak: Comparison of mechanical properties in compacted and spheroidal graphite irons, Tribology in Industry, Vol. 38, No. 1, pp 49-59, 2016.

[9] https://orange.biolab.si