La Metallurgia Italiana
International Journal of the Italian Association for Metallurgy

Neural networks-based prediction of hardenability of high performance carburizing steels for automotive applications

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The new quenching processes for automotive applications, which follow the cementation stage, include the application of pressurized gas for cooling during quenching. Therefore, it is of utmost importance to have an accurate estimate of the hardenability behavior of carburizing steels, which show a higher Carbon content with respect to traditional materials. These new cooling processes also require properly designed new steels in terms of alloying contents, which ensure a proper response to heat treatment.
In the present paper a neural network-based approach to the prediction of the hardenability profile is proposed, which can be applied both for the design of the steel chemistry and for assessing the suitability of the steel at the steel shop level, in order to suitable adjusting the cooling process after quenching.

KEYWORDS: LOW PRESSURE CARBURIZING - NEURAL NETWORK BASED PREDICTION - JOMINY END QUENCH TEST - TRANSMISSION GEARS

Introduction

Case hardening is a surface treatment able to confer a component elevated resistance to wear, fatigue and in general surface damage. Moreover, this treatment gives at the same time a high toughness at the core, thanks to the lower cooling speed, that is why it is commonly used for parts as transmission gear teeth and diesel fuel injectors. The process is typically applied to low carbon steels or low alloyed steels as Cr-Ni, Cr-Mo or Mn-Cr. These elements can be added to improve steel hardenability reaching a fully martensitic transformation till the core and thus sufficiently uniform mechanical properties.
Case hardening is a thermochemical diffusion treatment, it consists of a first heating of the component up to austenitizing temperature where the carbon enrichment of the surface is possible and diffusion within the steel is enhanced by the elevated carbon gradient from the surface to the core. This is followed by a quenching process and a low temperature stress relieving tempering.
The cementation can be carried out with different approaches, solid, salts bath and gaseous. Between these, the gaseous method is the most used because of process controllability and speed of the process itself. In this case the surface carburizing is due to carbon dissociation

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from a hydrocarbon (propane, acetylene or methane). The innovative variant of the treatment is the low-pressure carburizing (LPC), which is carried out at very low pressure using hydrocarbon gases and followed by high pressure gas quench.

This process allows constancy of metallurgical characteristics and lower deformations, surfaces without oxidizing products and no retained austenite. Clean surfaces lead to no need of cleaning products, resulting in lower cost for the treatment (1).

Case hardening steels standards are usually very restrictive in terms of Jominy curves, as the case of FCA internal material standard number (2).

The Jominy End Quench Test is very expensive and time consuming thus a lot of models to predict hardenability from the steel chemical composition have been proposed.

The first attempts were based on traditional statistical techniques, subsequently, more complex models based on Machine Learning (ML) techniques have been employed outperforming classical approaches. In particular, Artificial Neural Networks (ANN) have been successfully applied by providing very satisfactory predictive capabilities. In literature several approaches concerning ANN-based Jominy profile predictors have been proposed (3,6), which predict the steel hardness for each single point of the Jominy profile, while in (7,9) a parametric approach has been proposed and refined, which predicts each single point as part of a parametric curve, whose parameters are correlated to the steel chemistry.

A further relevant advancement is proposed in (10), where a sequantial ANN-based predictor is proposed, which provides not only the hardness value at each point but also an estimate of the reliability of such prediction.
This approach is also exploited within the present work for the simulation.

This model was used to optimize gaseous hardening steels chemical composition predicting and comparing Jominy curves. Chemical composition was varied in terms of alloying elements and concentration, focusing on Mn-Cr and Mn-Cr-B steels.
These steels can return a good compromise between mechanical properties and sufficient toughness, but they are a rational choice considering economical reason.

Materials and methods

Low carbon and low alloyed steels are usually used for case hardening process, to guarantee the major carbon gradient between surface and core.

Considering the low carbon content, some alloy elements are introduced in the chemical composition to increase the hardenability of the steel reaching a complete martensitic transformation also at the very core of the component.

For this study, some Jominy tests were industrially performed on various castings, considering the chemical ranges of FCA internal standard (Table 1). Jominy End Quench tests were carried out with reference to ASTM A255 (11).

Resulting hardness profiles did not match every time with desired ranges, in Figure 1 some examples were reported and the high deviation of results is evident.

Tab.1 - Chemical composition ranges (%), balance: Fe

C	Mn	Si	Cr	B	Ti	Cu	S	P	Al
0.23÷0.31	1.10÷1.40	0.10÷0.40	1.00÷1.30	≤0.0005	≤0.010	≤0.30	0.025÷ 0.040	≤0.030	0.015÷ 0.040

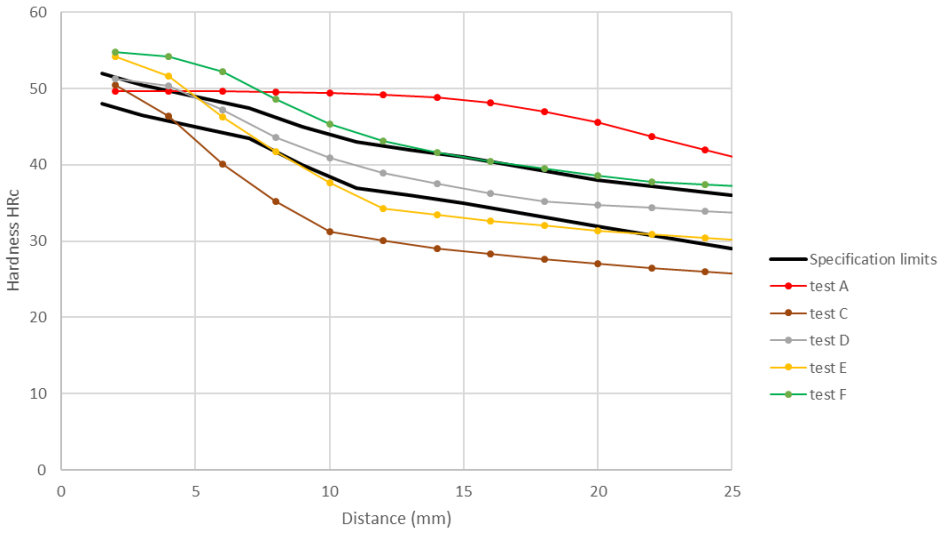

Fig.1 - Jominy curves returned on castings with FCA standard chemical composition

A comparison between test results and hardness ranges reported in FCA internal standards was made. Resulting hardness profile were often quite far from required ones, thus chemical composition was optimized by means of ANN-based (refer to paragraph 2). Chemical composition was varied within new chemical limits in accordance with Table 2, in particular Boron was added just to improve hardenability.

Tab.2 - Modified chemical composition ranges (%): balance: Fe

C	Mn	Si	P	S	Cr	Ni	Mo	Cu	Al	V	Nb	Ti	B
0.23÷ 0.31	1.10÷ 1.40	0.10÷ 0.40	≤0.030	0.025÷ 0.040	≤0.40	≤0.40	≤0.10	≤0.30	0.015÷ 0.040	0.003÷ 0.006	0.001÷ 0.003	0.045÷ 0.055	0.0025÷ 0.0035

Neural networks-based prediction of the Jominy profile

The Jominy profile prediction is performed by exploiting a set of 2-layers standard perceptron-based Feed-Forward ANNs according to the hierarchical structure, which is depicted in Figure 2.

The inputs and the number Nh of neurons in the hidden layer are different for each ANN and include the most correlated chemical elements and eventually the previously predicted hardness of other points of the Jominy profile.

The selection of the input variables to be used for the prediction of the different points of the profile has been performed both on the basis of some literature results related to the influence of chemical elements on the Jominy profile and of a preliminary statistical analysis aiming at highlighting the correlation between the potential input variables and the target hardness values(12,13).

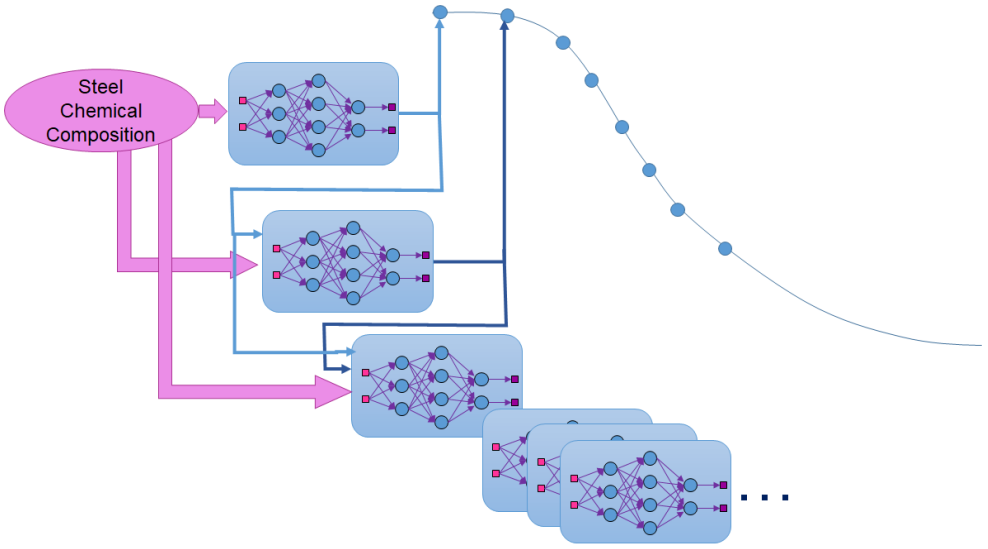

Fig.2 -Sequential structure of the Jominy profile predictor

Table 3 shows in detail the list of the inputs which are fed to each neural network for the prediction of specific Jominy profile points: each row of the table corresponds to one point and reports both the included chemical elements and the predicted hardness values fed as input to the ANN (where $\hat{J}_i$ represents the hardness value estimated at i-th distance value). Table 1 also reports the number of neurons in the hidden layer N_h of each ANN. The points of the Jominy profile are predicted in sequence in order to suitably exploit the relations between them. Due to the dependencies between single points expressed in Table1, the order of prediction is not the natural one, but the following order, which is more fruitful for the purpose of this work, is adopted: 1-2-3-4-5-14-15-13-12-11-10-9-8-7-6, where each number represents the corresponding profile point.

Tab.3 - Inputs of the ANNs of the Jominy profile predictor

Point	Input		N_h
	Chemical elements	Predicted hardness values	
J1	C, Mn, Si	-	2
J2	C,P,S,Cu	$\hat{J}1$	2
J3	C, Cr, S, Ni	$\hat{J}1$, $\hat{J}2$	3
J4	C, Cu, Mn, Mo	$\hat{J}2$, $\hat{J}3$	3
J5	C, B, Ti, Nb	$\hat{J}3$, $\hat{J}4$	4
J6	C, B, Ti, Nb	$\hat{J}2$, $\hat{J}5$, $\hat{J}7$	4
J7	C, B, Ti, Nb	$\hat{J}1$, $\hat{J}2$, $\hat{J}5$, $\hat{J}10$	4
J8	C, Sn, Al, V	$\hat{J}4$, $\hat{J}6$, $\hat{J}7$, $\hat{J}9$, $\hat{J}10$	4
J9	C, S, P	$\hat{J}2$, $\hat{J}3$, $\hat{J}5$, $\hat{J}11$	4
J10	C, S, P, Cu	$\hat{J}1$, $\hat{J}2$, $\hat{J}4$, $\hat{J}5$, $\hat{J}11$	3
J11	C, S, Cr, Ni	$\hat{J}1$, $\hat{J}4$, $\hat{J}5$, $\hat{J}12$, $\hat{J}15$	3
J12	C, Mn, Ni	$\hat{J}1$, $\hat{J}3$, $\hat{J}4$, $\hat{J}13$	3
J13	C, S, Cr, Ni, Nb,Ti, B	$\hat{J}1$, $\hat{J}4$, $\hat{J}5$	3
J14	C, P, S, Cr	$\hat{J}1$, $\hat{J}2$, $\hat{J}3$, $\hat{J}5$	3
J15	C, P, S, Cr	$\hat{J}1$, $\hat{J}3$, $\hat{J}5$	2

The ANNs are sequentially trained by means of the standard back-propagation algorithm by exploiting 600 randomly selected samples from an experimental dataset composed of about 1100 samples, while the other samples are used for validation. This dataset was available before the development of the analysis described in this paper, namely none of the data which have been used in the present work have been exploited in the training of the system. For the purpose of the analysis discussed here, the ANN-based Jominy predictor has been used simply as a "virtual hardenability test developer" and the goodness of the achieved results further demonstrates its general validity.

Results

Simulation results were analyzed to evaluate the goodness of resulting Jominy curves in comparison with desired hardness defined in the FCA standard.

For each Jominy position the error was calculated compared to the average value of the specification limits, consequently the average error, calculated on the whole curve, was estimated.

Thanks to this analysis a series of optimal and promising chemical compositions were defined.

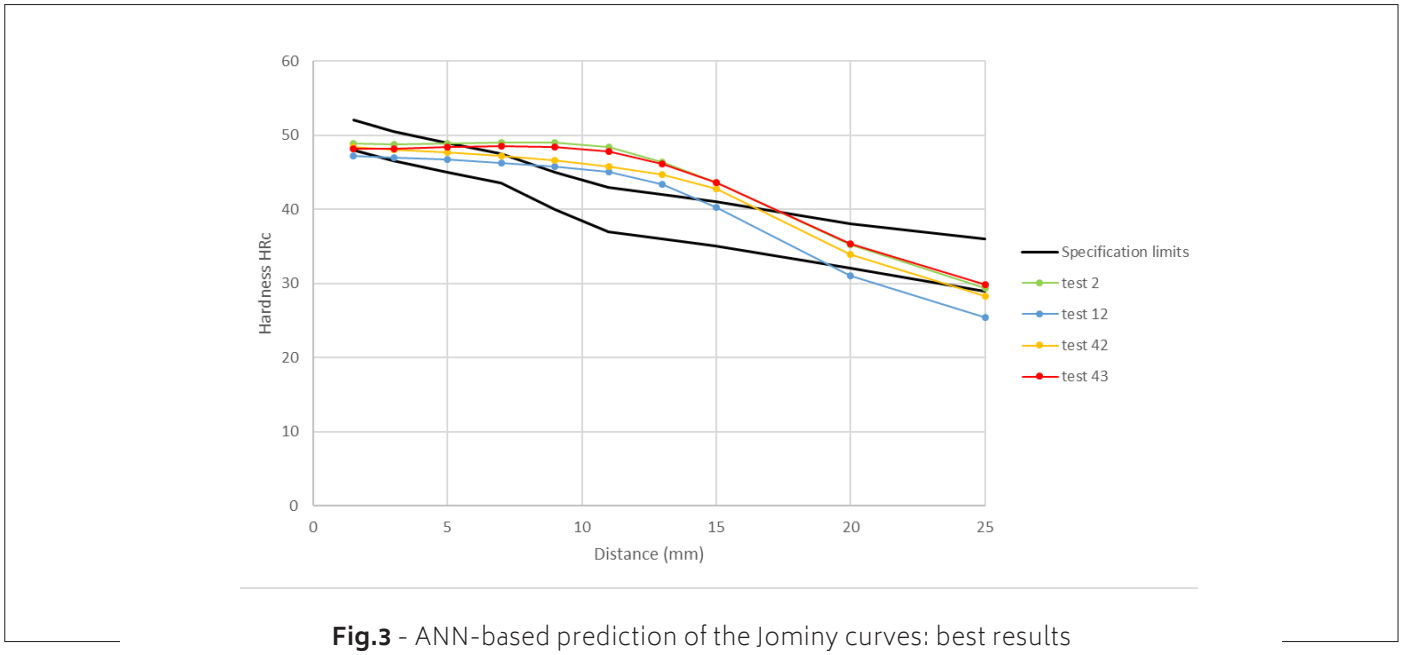

Fig.3 - ANN-based prediction of the Jominy curves: best results

To validate results also a series of Jominy tests were performed in plant. As an example, some of the curves with the lower average error were reported in Figure 2 and Figure 3, and the comparison of calculated errors was reported in Table 4.

Tab.4 - Average error estimation for Jominy hardness profiles compared to FCA reference standard

Test ID	Average error (HRc) Neural network-based prediction	Average error (HRc) Industrial tests
2	3.8	2.9
12	3.1	2.5
42	3.0	3.2
43	3.6	2.8

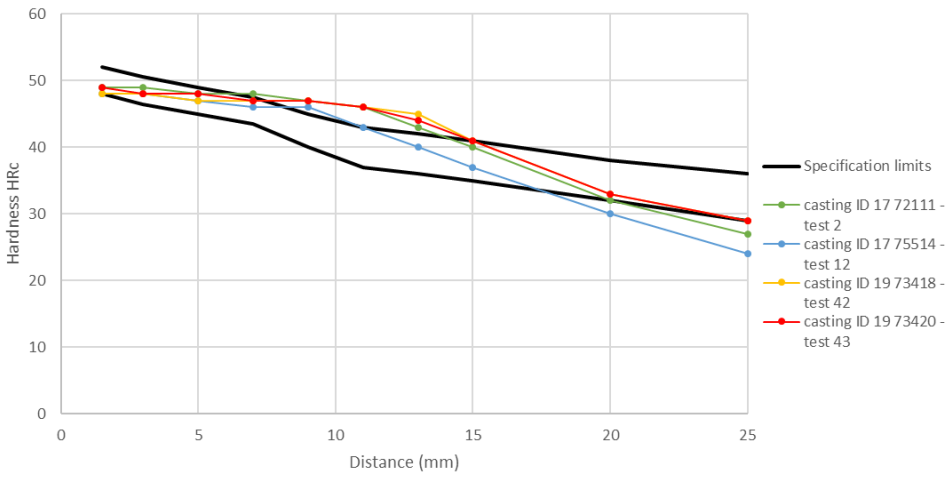

Fig.4 - Jominy results on casting with optimal chemical composition predicted by the ANN-based predictor

Conclusion

The present study was a preliminary investigation with the aim of optimizing production process for suitable steels for low pressure cementation. Considering the first results the following consideration can be gathered:

1) Usual chemical composition ranges are too wide to obtain components in accordance with severe automotive reference standards, that is why a specialization is required.

2) A properly trained neural network-based predictor could be a powerful tool to avoid a large number of experimental industrial tests.

3) The error that occurs with the ANN-based prediction has the same order of magnitude of experimental data dispersion on this category of steels.

4) The presented results lead to the development of steel for the specific application as a subgroup of MnCrB5 series. These steels have the certain advantage of a great economical convenience thanks to the absence of expensive alloy elements as Nickel or Molybdenum.

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