Determination of hot- and cold-rolling texture of steels: A combined Bayesian Neural Network model

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Abstract

The work reported in this paper outlines the use of a combined artificial neural network model capable of fast online prediction of textures in low and extra low carbon steels. We approach the problem by a Bayesian framework neural network model that take into account as input to the model the influence of 23 parameters describing chemical composition, and thermomechanical processes such as austenite and ferrite rolling, coiling, cold working and subsequent annealing involved on the production route of low and extra low carbon steels. The output of the model is in the form of fiber texture data. The predictions of the network provide an excellent match to the experimentally measured data. The results presented in this paper demonstrate that this model can help on optimizing the normal anisotropy (r_m) of steel products.

Keywords: Artificial Neural Network; Texture prediction; Anisotropy; Hot Rolling; Cold rolling; Steel

Introduction

In recent years there has been a steady increase of interest from the automotive industry in isotropic steel product; i.e. steel products with a minimum of variation of mechanical properties, most noticeably drawability, in the plane of the sheet. Therefore, corresponding to the ever increasing demands of the sheet metal forming industry, future generations of drawable steel grades will need to ensure a well-balanced equilibrium between drawability on the one hand and drawing anisotropy on the other hand.

Great demands are placed on the quality of deep drawing steels with regard to their surface and mechanical properties. The knowledge of the microstructural and textural evolution in the individual process stages is of highest importance to improve sheet quality in terms of its deep-drawing properties. In the past the derivation of models for microstructural and textural evolution was carried out on the basis of the results of laboratory tests using the reversing rolling technique. This applies in particular to the rolling experiments which can be performed at low rolling speeds only, e.g. approximately 1 ms^{-1} and inter pass times > 5 seconds.

Nevertheless, the continuously increasing requirements on the quality of flat products demand the further development of both materials and their production technologies. Such development can be achieved in modern continuous hot strip mills which operate with rolling speeds of up to 20 ms^{-1} and inter pass times of 0.1 s. From this follows, that differences in microstructure and properties existed between strips rolled in the laboratory and in practice, which reveals that laboratory plants and even pilot mills often cannot accurately simulate production conditions.

To close this gap, in this paper it was decided to employ an entirely new tool, patterned to human brain: the 'artificial neural networks'. Such networks 'learn' from the massive volume of incoming data and the relationships involved and gain experience from systematic observation of recurring events. This makes them capable of supporting traditional mathematical models or replacing them entirely. Their learning ability also enables neural networks to adapt continuously to changing process states. This paper illustrates the use of such modelling technique in the prediction of texture for low-carbon (LC) and extra low carbon (ELC) deep drawing steel qualities as a function of chemistry and thermomechanical processing parameters. The drawing properties of the steel are essentially determined by the texture of the finished product. The model is then used in the prediction of the normal anisotropy ratio, or the r_m value, for LC and ELC steel. The r_m value evaluates the drawability of a sheet material, i.e. its capacity to achieve a high degree of plastic flow in the plane of the sheet while offering sufficient resistance to flow in the thickness direction. On this basis, the work reported here provides an example of how neural network modelling could be incorporated into the optimization process of steel sheets and how the rolling processing parameters affects the texture of such steels that satisfy the increasing drawability of advanced steel for automotive applications.

Build of the model

The drawing properties of the steel are essentially determined by the texture of the finished product [1]. Figure 1 shows the $\phi_2 = 45^\circ$ sections of the ODF, because this section contains all the important rolling and recrystallisation components of a BCC material. The texture components depicted in Fig. 1 can be used as a key to read the texture results obtained by the model. In this figure it can be seen that the dominant components mainly concentrate along two fibers: α -fiber ($RD \parallel \langle 110 \rangle$), with main texture components within the range $\{001\}\langle 110 \rangle$ ($\phi_1=0^\circ$, $\Phi=0^\circ$, $\phi_2=45^\circ$) to $\{111\}\langle 110 \rangle$ ($\phi_1=0^\circ$, $\Phi=55^\circ$, $\phi_2=45^\circ$), and the γ -fiber ($ND \parallel \langle 111 \rangle$), where RD is the rolling direction and ND is the direction parallel to the sheet normal. It is commonly known that for a BCC material the γ -fibre $\langle 111 \rangle \parallel ND$ texture is the desired texture type to obtain the highest drawability. In consequence, texture control in drawing steel grades consistently aims to develop the highest possible intensity along the γ -fibre.

The texture strength has been modelled by determining the α - and γ - fibers intensities ($f(g)$). The α -fiber intensity has been calculated for $0^\circ < \Phi < 90^\circ$ in steps of $\Phi=5^\circ$. Each step corresponds to an independent neural network model. On the other hand, the γ -fiber has been calculated for $60^\circ < \phi_1 < 90^\circ$ in steps of $\phi_1=10^\circ$, with independent models for each step. Therefore, 19 different models have been developed to characterise the α -fiber, and 4 models to characterize the γ -fiber.

In this sense, the focus of this work was the investigation of the influence of rolling parameters on the α - and γ -fibers of hot strip, and derived cold strip, from ultra-low carbon (ULC), interstitial free (IF), low-carbon (LC), high-strength low-alloyed (HSLA), and extra-low carbon (ELC) steel grades. Figure 2 shows the product flow and the major characteristics of the hot and cold strip mill line. The following parameters were varied to investigate their effects on strip properties: roughing temperature and reduction, reheating temperature, finishing temperature and reduction, rolling speed, cooling conditions, coil temperature, and rolls with roll gap lubrication.

A second aim of this paper is to clarify the impact of the hot strip state on the properties of cold strip. In this sense, parameters such as cold rolling reduction and annealing temperature were systematically analysed and incorporated in the dataset. Likewise, special attention has been paid to the influence of hot-rolling on subsequent cold-rolled microstructure. The proposed model allows a more deep understanding of the influence of each parameter of the rolling stand (hot and cold rolling) on the final microstructure of deep drawable steels. Furthermore, this model allows a systematic development of new materials with regard to deep drawing properties depending on the deformation conditions.

Database

The models that constitute the α - and γ -fibers require a complete description of the chemical composition and processing parameters. A literature survey [2-9] allows us to collect 240 individual cases where detailed chemical composition, hot-rolling processing parameters, coiling temperature, cold reduction and annealing temperature values were reported for each of the 18 individual models which form the α -fiber, and the 4 individual models that form the γ -fiber. The hot-rolling data collected correspond to those obtained from pilot mill. The pilot mill comprises four rolling stands so arranged in one line that roughing is possible with one reversing two-high stand, followed by continuous finishing with all four stands (reversing two-high plus three continuous two-high stands). Samples are heated in an inductor allowing fast heating to 1350°C. All stands are equipped with roll gap lubrication, and interpass times can be varied by modification of the rolling speeds and the distances between stands. The hot-rolled samples are then cold-rolled and continuously annealed in a radiation furnace simulator.

The variables considered are the following: chemical composition in weight pct (carbon (C), manganese (Mn), silicon (Si), aluminium (Al), chromium (Cr), nitrogen (N), niobium (Nb) and titanium (Ti)), reheating temperature (SRT), roughing stage (temperature (RT), speed (RS), passes (nR) and reduction (RRED)), finishing stage (temperature (FT), speed (FS), passes (nF) and reduction (FRED)), the use of lubricant during rolling (LUB: without = 0; and lubricant = 1), coiling temperature (CT), cold-rolling reduction (CRED), and finally annealing temperature (AT)). Table 1 shows the list of 23 input variables used for the α - and γ -fibers analysis, and Table 2 lists the output variables considered.

Brief description neural network

The aim is to be able to estimate $f(g)$ evolution with Φ for α -fiber and with φ_1 for γ -fiber as a function of the variables listed in Table 1. In the present case, the network was trained using a randomly chosen of 130 examples from a total of 240 available; the remaining 110 examples were used as new experiments to test the trained network. Linear functions of the inputs x_j are operated by a hyperbolic tangent transfer function

$$h_i = \tanh \left(\sum_j w_{ij}^{(1)} x_j + \theta_i^{(1)} \right) \quad (1)$$

So that each input contributes to every hidden unit. The bias is designated $\theta_i^{(1)}$ and is analogous to the constant that appears in linear regression. The strength of the transfer function is in each case determined by the weight $w_{ij}^{(1)}$. The transfer to the output y is linear

$$y = \sum_i w_i^{(2)} h_i + \theta^{(2)} \quad (2)$$

This specification of the network structure, together with the set of weights, is a complete description of the formula relating the inputs to the output. The weights were determined by training the network and the details are described by MacKay [10-11]. The training involves a minimization of the regularized sum of squared errors.

The term σ_v was the framework estimation of the noise level of the data. Figure 3 shows, as an example, the inferred noise level of $\Phi = 45^\circ$ model. It is clear from the figure that the inferred noise level decreases monotonically as the number of hidden units increase. Table 2 list the σ_v values obtained for each model. However, the complexity of the model also increases with the number of hidden units. To find out the optimum number of hidden units of the model the following procedure was used. The experimental data were partitioned equally and randomly into a test dataset and a training dataset. Only the latter was used to train the model, whose ability to generalist was examined by checking its performance on the unseen test data. The test error (T_{en}) is a reflection of the ability of the model to predict in the test data:

$$T_{en} = 0.5 \sum_n (y_n - t_n)^2 \quad (3)$$

where y_n is the set of predictions made by the model and t_n is the set of target (experimental) values.

A high degree of complexity may not be justified, and in an extreme case, the model may in a meaningless way attempt to fit the noise in the experimental data. MacKay [12-13] has made a detailed study of this problem, and defined a quantity (the 'evidence') which comments on the probability of a model. In circumstances where two models give similar results for the known data, the more probable model would be predicted to be that which is simpler; this simple model would have a higher value of evidence. The evidence framework was used to control σ_v . The number of hidden units was set by examining performance on test data. A combination of Bayesian and pragmatic statistical techniques were therefore used to control the complexity of the model [14]. For the particular case of $\Phi = 45^\circ$ model shown in Figure 3, it could be concluded that a large number of hidden

units did not give significantly lower values of σ_v ; indeed, eleven hidden units were found to give a reasonable level of complexity to represent the variations of $f(g)$ as a function of the input variables of Table 1.

On the other hand, it is possible that a *committee* of models can make a more reliable prediction than an individual model. The best models were ranked using the values of their test errors (equation (3)) as Fig. 4(a)-(d) and Fig. 4(e) present, for the respective α -fiber and γ -fiber. Committee of models could then be formed by combining the prediction of the best L models, where $L = 1, 2, \dots$. The size of the committee is therefore given by the value of L .

The combined test error of the predictions made by a committee of L models, ranked $1, 2, \dots, q, \dots, L$, each with n lines of test data, is calculated in a similar manner to the test error of a single model:

$$T_{en} = 0.5 \sum_n (\bar{y}_n - t_n)^2$$

$$\bar{y}_n = \frac{1}{L} \sum_q y_n^{(q)}$$
(4)

where $y_n^{(q)}$ is the set of predictions made by the model and t_n is the set of target (experimental) values. As Figure 5 suggests the combined test error goes through a minimum for the committee made up of certain number of models as it is listed in Table 3. However, there some exceptions such as the one for $\Phi = 75^\circ$ and $\phi = 60^\circ$ models where the build of a committee does not reduced the test error. In such cases, the best model is considered only. From a comparison between results presented in Figures 4 and 5 it is clear a reduction in test error and hence improved predictions by using the committee of models approach instead of the best model alone. Comparison between the predicted and measured values of $\Phi = 45^\circ$ and $\phi = 60^\circ$, as an example, for the training and test data is shown in Fig. 6 for the best committee of each fiber component.

Nevertheless, the practice of using a best-fit function does not adequately describe the uncertainties in regions of the input space where data are spare or noisy. MacKay [12,13] has developed a particularly useful treatment of neural networks in a Bayesian framework, which allows the calculation of error bars representing the uncertainty in the fitting parameters. The method recognizes that there are many functions which can be fitted or extrapolated into uncertain regions of the input space, without unduly compromising the fit in adjacent regions which are rich in accurate data. Instead of calculating a unique set of weights, a probability distribution of sets of weights is used to define the fitting uncertainty. The error bars therefore become larger when data are spare or locally noisy.

Figures 7 and 8 illustrate the significance (σ_w) of each of the input variables, as perceived by the neural network, in influencing the components of α - and γ -fibers, respectively. The variables analysed are organized in three groups, i.e. Group 1: hot rolling, Group 2: chemical composition and Group 3: cold rolling and annealing (see Table 1). The value of σ_w is normalized to 100, i.e. the value of σ_w for a specific variable indicates the degree of influence in percentage. The metallurgical significance of the results predicted by the models is discussed below, but a first approximation of the influence of each one of the variables studied could be drawn from a close observation of Figs. 7 and 8.

As general comment for the 19 models of α -fiber components, and the 4 models of γ -fiber models, it is clear that the annealing temperature (AT) after cold rolling, together with cold-rolling reduction (CRED), clearly have a large intrinsic effect on α -fiber components, and in a minor scale on γ -fiber components. In terms of hot rolling processing parameters the finishing stage has a significantly larger influence than the roughing stage. Particularly, the slab reheating temperature (SRT) and the finishing temperature (FT) significantly affect the intensity of the α -fiber components for the case of $\Phi 0^\circ$ to $\Phi 20^\circ$ components. A relative low influence of those parameters is observed for the remaining components of α -fiber. It is also worth mentioning the lack of influence of *a priori* important variables such as finishing reduction (FRED), speed of rolling (FS) and the number of steps involved in the finishing process (nF).

On the other hand, finishing and roughing temperatures have a large influence on the components of γ -fiber, which is of technological importance since the intensity of such fiber is closely related with the deep drawing properties of the steels as it has been thoroughly reported in literature in the last decade.

Special attention to the role of chemical composition on the $f(g)$ values of α - and γ -fiber components has been paid. The chemical composition is not very relevant for the development of α -fiber components (with the exception of $\Phi 70^\circ$ component). However, it is important to highlight the spectacular relevance of microalloying elements such as Nb and Ti have on the intensity of γ -fiber components. This is consistent with the well reported influence of these microalloying elements on tying up the interstitial elements such as C and N, which have a negative influence on the development of good deep drawability properties. This broad idea is consistent with the high influence of C content in γ -fiber components, as it is seen in Fig. 8.

It is surprising the high influence that lubricant (LUB) has on $\Phi 0^\circ$ component of α -fiber, which could be related with the role of shear friction during rolling on the development of such component as it has been reported [15]. On the other hand, this parameter has a rather negligible influence on the remaining α - and γ -fiber components.

Applications of the model: Evolution of hot-rolling texture in IF steels

The effect of rolling parameters such as SRT, FS and FT on a IF steel is reported in this section (see Table 4 for chemical composition). It has been considered two situations: IF steel hot rolled in the austenitic (FT = 930 °C) as well as in the upper (FT = 800 °C) and lower ferritic region (FT = 650 °C). For the ferritic rolling a high and a low reheating temperature of 1250 °C respective 1050 °C have been investigated. Two different rolling speeds in the finishing mill have been considered (0.5 and 7 m s⁻¹).

Figure 9 shows the evolution of both alpha and gamma fibres for the two SRT selected. The FT value considered in calculations is 930 °C and FS = 0.5 m s⁻¹. The remaining rolling parameters considered are listed in Table 4. It is clear from the results presented that simulations are consistent with the typical low intensities on their alpha and gamma fibre expected after hot rolling processing. It could be concluded that there is not significant influence of SRT on hot-rolling texture.

On the other hand, Figure 10 presents the results for the influence of FT on hot-rolling texture. It has been selected three different temperatures. A FT of 930 °C which indicates an austenitic rolling and subsequent air-cooling to room temperature, and FT values of 800 and 650 °C for the upper and lower ferrite region with the higher reheating temperature of 1250°C (see Table 4 for remaining processing parameters). Compared with austenitic rolling the intensities are significantly higher both for the alpha and the gamma fibre. Significant differences of the intensities can be observed especially for the alpha fibre but also for the gamma fibre with FT in the ferrite-region. However, they could not be linked to an influence of rolling parameters such as SRT, RT and LUB. The attempt to link the differences to the roll speed fails. Figure 11 shows the differences in both alpha and gamma fibres with FS for a FT = 800 °C (see Table 4 for remaining parameters).

Applications of the model: Effect of chemical composition and processing parameters on the normal anisotropy index (r_m) in DDQ steels

On deep drawability quality (DDQ) steel, particular attention to {111}<uvw> orientation should be paid [16-17]. It has been demonstrated that high r_m values are displayed by materials which have a high proportion of grains oriented with their {111} planes parallel to the sheet plane, i.e. by materials which possess a strong {111} type texture (or γ -fibre texture). Other texture components, such as the {001}, have been found to be detrimental to the drawability and, in this sense, and according with the work reported by Daniel and Jonas [18], the most desired texture components to obtain good drawability properties are {111}<110> and {111}<112>, and the most undesired ones will be {110}<001> and {001}<110>. In practice, the intensity ratio of the above two

components, $I(111)/I(100)$, is found to be linearly related to r_m as it was determined by Held [19]. This author measured the evolution of r_m with the α - and γ -fibres intensities ratio, and concluded that there is a linear relationship expressed by

$$r_m = 0.8 + 0.6 \log \left(\frac{I(111)}{I(100)} \right) \quad (5)$$

Therefore, the influence of different processing parameters (and chemical composition) on r_m can be evaluated through the $I(111)/I(100)$ ratio by means of the neural network model developed in this work. Table 5 lists the conditions considered in calculations. More precisely, it has been considered two alternative processing routes denoted as ‘hot rolling’ and ‘cold rolling and annealing’. The former consist on processing the material as it is done in a traditional hot-rolling mill, meanwhile two additional stages (cold rolling deformation with a thickness reduction of 80%) and annealing temperature are added to the latter one. Those varying parameters are indicated.

Effect of chemical composition

Figure 12 shows the evolution of r_m for carbon content ranging from 0.002 wt% to 0.02 wt%. Constant values of Nb and Ti contents (i.e, [Nb] = 0.029 wt% [Ti] = 0.037 wt%) have been considered. Regarding the processing parameter, fixed values of finishing rolling temperature (FT = 930 °C), coiling temperature (CT = 700 °C), and annealing temperature (AT = 750 °C) have been used in calculations. The first conclusion that can be drawn from this figure is the significantly higher r_m value for a cold-rolled and annealed material as compared with a hot-rolled one, which is a consequence of the dramatic texture differences between hot-rolled and cold-rolled and annealed steels. The recrystallisation of austenite during hot rolling (with a FT = 930 °C) is unimpeded in and is sufficiently rapid to be essentially completed before the transformation to ferrite. This leads to an absence of texture components in the ferrite, since austenite did not contain any rolling components before transformation [20]. However, the cold rolling process induces a stored energy in the material that it is released during subsequent annealing treatment leading to the formation of deformation-free grains (recrystallization). On the basis of stored-energy considerations, the final texture should be dominated by nuclei which form soonest and which are most numerous. On this basis, the {111} components and a spread of random orientation may be expected, together with a small {110} component, in the cold-rolled and annealed steel as compared with hot-rolled one. This leads to a stronger $I(111)/I(100)$ ration and hence to a bigger r_m value.

Figure 12 also shows a decrease of r_m as C-content increases for cold-rolled and annealed steel. This result is fully consistent with work reported by Fukuda [21] where showed that r_m increased progressively with decrease in the amount of carbon. These effects have subsequently been corroborated by other workers [22] and confirm the broad idea that high levels of carbon were undesirable in deep drawing quality steels, which can probably be attributed to unfavorable annealing texture components nucleated around the harder second-phase pearlite islands.

Figures 13 and 14 show the influence of Ti and Nb additions on r_m values. The C content in both calculation is kept constant with a value of $[C] = 0.002$ wt%, $FT = 930$ °C, $CT = 700$ °C, and $AT = 750$ °C. It is clear that in both cases the annealed microstructure presents a significant increase in r_m value as the content of both Ti and Nb increases. On the other hand, there is an opposite effect in the hot-rolled microstructure. Meanwhile an increase in Ti content raises the value of r_m , an equivalent increase in Nb content induce a drop in r_m value. These results are consistent with the work reported by Hook and co-workers [23-24], where it was concluded that the austenite in the Nb steel is essentially pancaked (unrecrystallised), while the austenite is partially recrystallised in the Ti steel. The retardation of austenite recrystallisation in the Nb steel during hot rolling is attributable to two complementary factors: (a) the presence of solute Nb in the austenite, and (b) the precipitation of Nb carbonitrides in the matrix. Finally, as it is well know [25,26], the unrecrystallized austenite leads to a finer microstructure after austenite-to-ferrite transformation, and the finer the microstructure the lower the $I(111)/I(100)$ ratio [27], which can explain the decrease of r_m value in Nb-bearing steels as compare with Ti steels after the hot rolled stage.

Regarding the cold rolled and annealed results, it is clear that both Ti and Nb increase the r_m value. This is because of the very effective role of both Nb and Ti on tying up the interstitials in the steels. If the carbon in solid solution is tied up by Nb or Ti, an extensive recovery goes on the gamma grains and the local areas of high concentration of deformation energy quickly become potential nuclei of $\{111\}$ orientation. This strengthens the γ -fiber and hence the $I(111)/I(100)$ ratio increases. However, if the amount of carbon is high (not enough Ti and/or Nb in solid solution), the recovery is sluggish due to C-Mn dipoles immobilizing dislocations. In such a case the grains of lower concentration of deformation energy grow at expense of the highly deformed $\{111\}$ grains through a process of stress induced boundary migration. Therefore, the $I(111)/I(100)$ ratio is weakened, and hence r_m decreases.

Effect of processing parameters

The values of C, Ti and Nb considered in calculation are, respectively, $[C] = 0.002$ wt%, $[Ti] = 0.037$ wt% and $[Nb] = 0.029$ wt%. A value of coiling temperature of $CT=700$ °C has been considered in predictions. Figure 15 shows the influence of FT on r_m value for both hot-rolled and cold-rolled and annealed materials. It is worth

mentioning that the FT values considered here include both the austenitic and ferritic rolling. The observed increase of r_m value as FT decreases is related with the fact that at low FT values the steel is fully transformed to ferrite. The situation is therefore comparable with warm ferritic rolling procedure where rolling takes place in a ferritic stage. Thus, the formation of shear bands occurs which promotes the formation of dynamically recovered grains of $\{111\}$ orientation enhancing the development of a strong γ -fiber texture [28]. This is consistent with the increase in r_m value observed.

Regarding the evolution of cold-rolled and annealed material, a more complex behavior is observed. There is a maximum for a FT value of 850 °C which is the lowest FT to ensure a complete austenitic rolling. In the austenitic rolling regime, lower FT induces an unrecrystallized austenite which promotes the formation of a very fine ferrite grains during subsequent austenite-to-ferrite transformation. During annealing after cold-rolling, the $\{111\}$ grains nucleate in the grain boundaries of deformed ferrite grains. Therefore, the finer the deformed ferrite grain, the more abundant $\{111\}$ nucleation events. Thus, the γ -fibre strengthens with the concomitant increase in r_m value. This can explain the increase of r_m when FT is lowered in the austenitic rolling regime.

However, as it was reported by Jeong [29], ferrite grain after hot-rolling markedly coarsens with a decrease in the FT. When the FT is lower than A_{r3} , the grain structure just after hot-rolling in two phase region of ferrite and austenite consists of the deformed ferrite and deformed austenite grains. The deformed austenite grains immediately transform to strain-free ferrite grains which grow to the surrounding deformed ferrite grains during cooling and coiling simulation at 700 °C, leading to the coarse-grained structure. The microstructural change with the finishing temperature in hot-rolling is partially responsible for the change in the textural evolution during the subsequent cold-rolling and annealing, since cold-rolled microstructure is still reflecting the coarse structure of the hot-rolled steel. Therefore, the formation of $\{111\}$ grains at grain boundaries of deformed ferrite grains is overcome by a stronger development of the $\{100\} \langle 011 \rangle$ orientation in the annealed sheet, leading to a subsequent decrease in r_m values.

Figure 16 shows the effect of CT on r_m value. Regarding the hot rolled material, the effect of CT is negligible. Only a slight increase of r_m is observed at low CT values. However, a clear influence on cold-rolled and annealed material is observed. This behavior is consistent with experimental observations [30-31], where it was reported that final textures are improved by coiling the hot band at high temperature, i.e. above about 700°C. With high-temperature coiling, the carbide precipitation occurs during very slow cooling of the coiling, and the carbide constituents become coarser and more widely dispersed. Therefore, the ferrite becomes almost completely pure, since any residual carbon diffuses to the cementite particles and precipitates out [32-33]. If these carbides are widely spaced and if the steel is heated rapidly after cold rolling, it is possible for recrystallization

of the ferrite to take place before significant re-solution of the carbon can occur. The resulting texture contains a strong {111} component, and hence a high r_m value.

Figure 17(a) shows the evolution of r_m value with annealing temperature after cold-rolling (80% reduction in thickness). It could be concluded from the figure that the higher the annealing temperature the higher the r_m value. This is consistent with the work reported by Petite et al. [27] which demonstrated that there is a linear relationship between the recrystallized grain size and the r_m value. Therefore, the higher the annealing temperature, the coarser the grain grows and hence higher values of r_m are achieved.

On the other hand, the carbide dispersion formed during coiling is very important since coarse carbides are very effective on wiping out carbon from ferrite matrix, but fine dispersion of carbide particles produced by low-temperature coiling can release carbon into the matrix during cold rolling by a kind of mechanical-dissolution process. According to this view, the dissolved carbon causes dynamic strain aging and leads to inhomogeneous (constrained) deformation in the form of shear bands, which, on subsequent annealing, induce nucleation of unfavorably oriented grains [34]. The fact that carbon can operate in two different ways, i.e. during deformation and during annealing, is highly confusing. In order to clarify this combined effect, Fig. 18 shows the combined influence of CT and AT on r_m values. It is clear from the figure that the best result in terms of high r_m value is obtained at high-CT combined with high-AT values, where the coarser carbides are formed and the fast recrystallization will avoid the nucleation of some unfavorable recrystallized grains around the coarser carbides [35-36].

Conclusions

A combined neural network under a Bayesian framework has been developed to predict the texture evolution in low and extra low carbon steels. This model consists in the combination of 23 individual neural network models to deal with the evolution of α -fibre and γ -fibre by varying 23 input parameters describing chemical composition, and thermomechanical processes such as austenite and ferrite rolling, coiling, cold working and subsequent annealing involved on the production route of low and extra low carbon steels. The predictions of the network within the bounds of the training data set show a good match to the measured values, allowing us to conclude that this combined model is a powerful tool for fast online prediction of textures in an engineering environment.

The combined neural network model created has been applied to predict the evolution of anisotropy index (r_m) in DDQ steels with varying chemical composition (C, Ti and Nb content) and processing parameters such as finishing rolling temperature (FT), coiling temperature (CT), and annealing temperature (AT) after cold-rolling.

The results obtained allow us to conclude that cold-rolling and annealing processing present a substantially higher r_m value as compare with hot rolling processing.

The model presented in this paper has been revealed very useful on predicting the influence that C, Ti and Nb in solid solution exert on r_m value. Higher carbon levels in solid solution are associated with weaker textures, reducing the r_m value. On the other hand, the Ti and Nb content substantially increase the r_m value.

The perception of the model to varying values of FT, CT and AT is consistent with measurements reported in literature. Particular attention to the effect of CT and AT has been paid. It has been demonstrated that r_m value is very sensitive to both parameters. The low-CT temperature allows higher amounts of carbon to remain in solid solution in ferrite, and then has a detrimental effect on r_m values. Meanwhile high CT leads to sharper {111} fibre and improved r_m values.

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Table 1. Variables that influence texture. SD is standard deviation

		Min	Max	Average	SD
Group 1	C, wt.%	0.0019	0.055	0.0167	0.0196
	Mn, wt.%	0.097	0.25	0.1819	0.0463
	Si, wt.%	0	0.071	0.026	0.0262
	P, wt.%	0.003	0.011	0.007	0.0026
	S, wt.%	0.004	0.013	0.008	0.0026
	Al, wt.%	0.015	0.049	0.0409	0.0082
	Cr, wt.%	0	0.027	0.0203	0.0076
	N, wt.%	0.0018	0.0049	0.0025	0.0008
	Nb, wt.%	0	0.029	0.0121	0.0124
	Ti, wt.%	0	0.041	0.0137	0.0162
Group 2	RT, °C	900	1200	1016.1506	82.3259
	nR	2	7	2.5439	1.1583
	RS, m s ⁻¹	0.5	4	1.2109	0.7269
	RRED, %	30	80	38.4161	15.021
	SRT, °C	1050	1250	1155.8996	96.7015
	FT, °C	535	950	837.0167	98.5536
	nF	1	4	3.7908	0.6467
	FS, m s ⁻¹	0.5	7	3.2331	1.8317
	FRED, %	48	98.6	86.3158	6.9489
	LUB	0	1	0.4979	0.501
Group 3	CT, °C	400	730	668.7531	102.413
	CRED, %	0	90	51.6987	38.6548
	AT, °C	20	830	388.9749	365.5413

Table 2. Output variables considered on describing α and γ fibers. SD is standard deviation. σ_v is the inferred noise level. $\Phi_{##}$ indicates the model corresponding to each 5°-step in $0^\circ < \Phi < 90^\circ$ for α -fiber. In the same sense, $\phi_{##}$ indicates the model corresponding to each 10°-step in $60^\circ < \phi < 90^\circ$ for γ -fiber.

	Min	Max	Average	SD	σ_v
$\Phi 0$	0	21	6.2731	5.217	0.12592
$\Phi 5$	0	22	6.3916	5.2351	0.11728
$\Phi 10$	0	24	6.5421	5.2321	0.10535
$\Phi 15$	0	24	6.6196	5.0916	0.08901
$\Phi 20$	0	24	6.6836	4.9716	0.09034
$\Phi 25$	0	24	6.7324	4.9775	0.09668
$\Phi 30$	0	23	6.7132	4.9826	0.09731
$\Phi 35$	0	22	6.7113	4.9549	0.09499
$\Phi 40$	0.5	35	6.6881	4.8271	0.047376
$\Phi 45$	0.5	15	6.3453	3.4699	0.080105
$\Phi 50$	0	13	6.0516	2.8367	0.10696
$\Phi 55$	0	15	5.4109	3.039	0.085474
$\Phi 60$	0	14	4.1294	2.6751	0.065997
$\Phi 65$	0	10	2.6394	1.8149	0.056186
$\Phi 70$	0	25	1.7011	1.8263	0.061479
$\Phi 75$	0	3	1.1913	0.6911	0.10554
$\Phi 80$	0	10	0.9256	0.8861	0.064904
$\Phi 85$	0	3	0.6592	0.6411	0.11
$\Phi 90$	0	4	0.6001	0.7078	0.1148
$\phi 60$	0.5	15	6.0456	2.966	0.056756
$\phi 70$	0	25	6.2615	1.8263	0.060707
$\phi 80$	0	22	6.7956	4.1269	0.06085
$\phi 90$	0	22	7.0367	4.4081	0.066218

Table 3. Models in committee for each of the components of α -fiber and γ -fiber.

Fiber component	N° models in committee	Fiber component	N° models in committee
$\Phi 0$	6	$\Phi 60$	3
$\Phi 5$	13	$\Phi 65$	3
$\Phi 10$	12	$\Phi 70$	11
$\Phi 15$	3	$\Phi 75$	1
$\Phi 20$	5	$\Phi 80$	2
$\Phi 25$	4	$\Phi 85$	2
$\Phi 30$	2	$\Phi 90$	9
$\Phi 35$	4	$\phi 60$	1
$\Phi 40$	4	$\phi 70$	2
$\Phi 45$	4	$\phi 80$	3
$\Phi 50$	3	$\phi 90$	2
$\Phi 55$	7		

Table 4. Chemical composition (in wt.%) and parameters used to study the evolution of hot-rolling texture.

C, wt.%	0.022
Mn, wt.%	0.14
Si, wt.%	0.071
P, wt.%	0.008
S, wt.%	0.004
Al, wt.%	0.047
Cr, wt.%	0.026
N, wt.%	0.002
Nb, wt.%	0.029
Ti, wt.%	0.037
RT, °C	1050
nR	2
RS, m s ⁻¹	0.5
RRED, %	30
SRT, °C	1250 / 1050
FT, °C	930 / 800 / 650
nF	1
FS, m s ⁻¹	0.5 / 7
FRED, %	48
LUB	1

Table 5. Chemical composition (in wt.%) and parameters used to study the evolution of r_m value. The term “Varying” stands for varying conditions of this particular parameter.

	‘hot-rolled’	‘Cold-rolled & Annealed’
C, wt.%	varying	varying
Mn, wt.%	0.14	0.14
Si, wt.%	0.071	0.071
P, wt.%	0.008	0.008
S, wt.%	0.004	0.0026
Al, wt.%	0.047	0.047
Cr, wt.%	0.026	0.026
N, wt.%	0.002	0.002
Nb, wt.%	varying	varying
Ti, wt.%	varying	varying
RT, °C	1050	1050
nR	2	2
RS, m s ⁻¹	0.5	0.5
RRED, %	30	30
SRT, °C	1250	1250
FT, °C	varying	varying
nF	1	1
FS, m s ⁻¹	0.5	0.5
FRED, %	48	48
LUB	1	1
CT, °C	varying	varying
CRED, %	0	80
AT, °C	20	varying

Figure 1. $\varphi_2 = 45$ section of Euler space showing the ideal BCC rolling and recrystallisation components

Figure 2. Scheme of hot and cold rolling mills for steel production

Figure 3. Variation of inferred noise level (σ_v) as a function of the number of hidden units for $\Phi = 45^\circ$ model.

Figure 4. Test error values of the twenty best models for (a) α -fiber (Φ between $0^\circ - 20^\circ$), (b) α -fiber (Φ between $25^\circ - 40^\circ$), (c) α -fiber (Φ between $45^\circ - 65^\circ$), (d) α -fiber (Φ between $75^\circ - 90^\circ$), and (e) γ -fiber models.

Figure 5. Combined test error values of the committee for (a) α -fiber (Φ between $0^\circ - 20^\circ$), (b) α -fiber (Φ between $25^\circ - 40^\circ$), (c) α -fiber (Φ between $45^\circ - 65^\circ$), (d) α -fiber (Φ between $75^\circ - 90^\circ$), and (e) γ -fiber models.

Figure 6. Comparison between the predicted and measured values of (a) $\Phi = 45^\circ$ and (b) $\phi = 60^\circ$ using their respective committee of models.

Figure 7. Histogram showing the significance of input variables in influencing the α -fiber components perceived by their respective best models.

Figure 8. Histogram showing the significance of input variables in influencing the γ -fiber components perceived by their respective best models.

Figure 9. Influence of SRT on hot-rolling texture (a) alpha and (b) gamma fibre.

Figure 10. Influence of FT on hot-rolling texture (a) alpha and (b) gamma fibre.

Figure 11. Influence of FS on hot-rolling texture (a) alpha and (b) gamma fibre.

Figure 12. Effect of C content on r_m .

Figure 13. Effect of Nb content on r_m .

Figure 14. Effect of Ti content on r_m .

Figure 15. Effect of FT temperature on r_m .

Figure 16. Effect of CT temperature on r_m .

Figure 17. Effect of AT temperature on r_m .

Figure 18. Combined effect of CT and AT on r_m value.

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(a)

(b)

(c)

(d)

(e)

Figure 4. Test error values of the twenty best models for (a) α -fiber (Φ between 0° - 20°), (b) α -fiber (Φ between 25° - 40°), (c) α -fiber (Φ between 45° - 65°), (d) α -fiber (Φ between 75° - 90°), and (e) γ -fiber models.

(a)

(b)

(c)

(d)

(b)

Figure 5. Combined test error values of the committee for (a) α -fiber (Φ between 0° - 20°), (b) α -fiber (Φ between 25° - 40°), (c) α -fiber (Φ between 45° - 65°), (d) α -fiber (Φ between 75° - 90°), and (e) γ -fiber models.

(a)

(b)

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(a)

(b)

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(a)

(b)

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(a)

(b)

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