

Artificial Neural Networks to correlate Hot Deformation Cooling Rate and Deformation Temperature on Continuous Cooling Transformation of 22MnB5 Steel

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Abstract: - The 22MnB5 steel is a hot stamping steel developed with the aim to satisfy the increasing request of the automotive industries to apply materials able to guarantee higher passive safety and weight reduction. The hot stamping process is an innovative forming technique in which the deformations are carried out at elevated temperature and allows to achieve high strength components. The experimental characterization of the material response, at different values of the main variables of process, may result both expensive and time consuming, but the mutual effects evaluation of the deformation parameters and the phase transformations are necessary to produce components within the desired properties. The developed model, by means of a neural network approach with a Bayesian framework, is able to predict the hardness and the specific microstructure of 22MnB5 steel as a function of the main parameters that are fundamental in hot stamping processes, thus overcoming the lack of fit of the existing numerical models.

Key-Words: - Artificial Neural Network, 22MnB5, Continuous Cooling Transformation, Hot Prestrain.

1 Introduction

The 22MnB5 steel is a hot stamping steel developed in the last years from the steels manufacturers with the aim to satisfy the increasing request of the automotive industries to apply materials able to guarantee higher passive safety and weight reduction.

The hot stamping process is an innovative forming technique in which the deformations is carried out at elevated temperature, when the steel is in its austenitic phase, and allows to achieve, finally, high strength steel components. The necessity to put inside the dies the hot steel and to form and quench it in only one step, makes the process strongly dependent from the forming temperature, the strain value and the cooling rate. The experimental characterization of the material response at different values of the main variables of process, may result both expensive and time consuming, but the evaluation of the mutual effects of the deformation parameters and the phase transformations is necessary to produce components with the desired properties [1-3].

Recently different constitutive numerical models to evaluate the material response of 22MnB5 steel

subjected to thermo-mechanical cycles that simulate the hot stamping conditions have been developed. As described in the following section, for each proposed constitutive model, it is possible to identify a range of thermo-mechanical parameters in which a lack of fit between the experimental and modelled data appears.

The Neural Networks tool offers a forecasting method that can overcome the lack of fits of numerical models and moreover, can model the phase transformations phenomena influenced by strong non linear factors. Although there are some applications of neural network approach to predict the materials phase transformations under different thermal cycles, there is a failing of researches that apply this modelling tool considering thermomechanical cycles [4-6].

The aim of the conducted study is to develop a model able to predict the hardness and the specific microstructure of 22MnB5 steel as a function of main parameters that are influent in hot stamping processes using a neural network approach with a Bayesian framework.

2 Fundamentals

Phase transformations occurring during thermo-mechanical cycles may be well understood using quantitative and qualitative microstructural investigations, by recognizing existing phases and fractions of each phase. Furthermore the hardness level of each phase suggests to use this parameter to identify the phase heterogeneity.

Hot stamping is a non-isothermal forming process for sheet metal alloys, where forming and quenching take place in one combined step. The best cooling rate for quenching 22MnB5 steel is determined by the conditions that avoid transforming the austenite into ferrite, pearlite and bainite.

The boron content of 22MnB5 steel acts as hardening agent during thermo-mechanical treatments and provides a material with excellent hardness and strength. The quenching treatment, usually performed on these materials, determines the heterogeneous precipitation of boron carbide at the grain boundaries and also the boron segregation. The segregation phenomenon causes increasing hardenability of the material by suppressing the austenite to ferrite transformation. Substitutional solid solution elements, such as Mn, is known to only slightly influence the strength after quenching; however Mn is essential for securing hardenability [7-9].

The prior austenite grain size is fundamental on beginning the diffusion transformations. When the austenite grain size becomes smaller, or the heating temperature becomes lower, the transformations into these phases take place quicker and, as a consequence, the cooling rate for the quenching must be higher.

Based on these considerations, the complete modelling of these steels, when subjected to hot stamping processes, needs to start from a wide experimental database on the microstructural and mechanical effect of the main process parameters. The experimental reproduction of the hot stamping process conditions is achievable performing hot compression or tensile tests stopped at different strain levels and followed by different cooling paths.

2.1 The existing numerical models

The numerical description of the high temperature behaviours of hot stamping steels can take advantage of two main formulations, as reported in literature researches, the Voce-Kocks combined model and the Molinari-Ravichandran model [10].

The Voce model is suitable for polycrystalline materials in which saturation stress appears at large deformations. Nevertheless this model is strain rate and temperature insensitive; the coupling of this formulation with the kinetic Kocks model provides a forecasting tool able to describe the mechanical behaviour of material considering both the influence of the strain rate and the temperature.

The Molinari-Ravichandran (MR) model is based on a single internal variable that is related to the microstructural evolutions during the deformation process and it is strain rate and temperature sensitive.

The main disadvantage of both models is their inability to include two aspects, moreover evidenced from the experimental results, as the static thermal recovery and the dynamic recrystallization. Furthermore, the forecasting accuracy of each model is strongly dependent of the considered range of temperature or strain and requires the evaluation of many independent adjustable parameters.

The fitness of Voce-Kocks model increases at low temperature and strain rate values but at elevated temperature the model is suitable when the strain rate increase. The MR model capability to fit the experimental data decreases at elevated temperature and this occurrence appears at all the strain values. These forecasting gap suggested to develop a microstructural prediction tool that overcomes the necessity to translate all the complexities of the considered system into constitutive formulations.

2.2 The Neural Networks technique

The artificial neural network approach constitutes a regression analysis method in which a flexible non linear function is fitted to the experimental data. This tool is able to capture complex relationships characterizing phase transformations, without requiring the mathematical descriptions of phenomena.

The Bayesian framework applied to the neural model is able to take into account the fitting uncertainty. The method calculates a probability distribution of the set of neural network weights and provides the outputs error bars, defining the applicability range of neural model. Furthermore, the significance of the input variable is automatically quantified.

Considering the Kolmogorov theorem, the complexity of each system can be captured with a neural network model containing a single hidden layer; the flexibility of model is attained operating on the number of the hidden units. The general model formulation considering a feed-forward

architecture with one hidden layer and i hidden units is:

$$y_k = \sum_i w_{ki}^{(2)} h_i + \theta_k^{(2)} \quad (1)$$

$$\text{where } h_i = \tanh\left(\sum_j w_{ij}^{(1)} x_j + \theta_i^{(1)}\right) \quad (2)$$

x_j are the inputs, y_k are the outputs, θ are the bias corresponding to each neural node, w are the neural weights, the superscript (1) is referred to the hidden layer, whereas the superscript (2) is referred to the output layer. The equation (1) expresses the output of the neural model, whereas the equation (2) expresses the transfer function. The combine of several hyperbolic tangents confers to the model the ability to capture non linear relationship between inputs and outputs [11-14].

The number of input, output and hidden nodes and their connections defines the architecture of the neural model. The Bayesian framework foresees that the weights and biases of the network are assumed to be random variables with specified distributions and provides a method to improve the generalization capability of neural network usually called regularization.

Backpropagation algorithm is able to train multilayer feed-forward networks with differentiable transfer functions to perform function approximation, pattern association, and pattern classification. There are several backpropagation training algorithms; among them, the Bayesian regularization one consists in a modification of the Levenberg-Marquardt training algorithm to produce networks that generalize well reducing the difficulty of determining the optimum network architecture.

The Bayesian regularization involves modifying of the performance function, which normally is the sum of squares of the network errors on the training set. The formulation of the Bayesian performance function is depicted in the following equation (3):

$$MSE_{reg} = \gamma MSE + (1-\gamma) MSW \quad (3)$$

in which MSE_{reg} is the modified performance function, γ is the performance ratio, MSE is the typical performance function mean squared error given by:

$$MSE = \frac{1}{N} \sum_{i=1}^N (e_i)^2 = \frac{1}{N} \sum_{i=1}^N (t_i - y_i)^2 \quad (4)$$

in which $t_i - y_i$ represents the difference between the target value and the output value and MSW is the mean of the sum of squares of the network weights:

$$MSW = \frac{1}{n} \sum_{i=1}^n (w_j)^2 \quad (5)$$

The determination of the optimum value for the performance ratio parameter (γ) allows to generate a network that best fits the training data. In effect, if this parameter is too large, it may get overfitting and if the ratio is too small, the network will not adequately fit the training data.

The described network architecture has been implemented using the MATLAB neural network toolbox that provides some routines that automatically sets the regularization parameters. The Bayesian regularization work well if the input and the target data are ranged in [-1;1]. Therefore, the inputs and the targets have been normalized within the range [-1;1] before training as follows:

$$x_{norm} = 2 \frac{x - x_{min}}{x_{max} - x_{min}} - 1 \quad (6)$$

where x_{norm} is the normalized value of each parameter, x , x_{min} and x_{max} are respectively the measured, the minimum and the maximum values for the considered parameter. In order to avoid the possibility of overfitting data, the experimental data are randomly divided into two groups respectively called training set and test set. The model has been implemented considering the only training data set constituted by 75% of the experimental data and it has been validated considering the test data set constitute by 25% of the experimental data.

3 Application of Model and Results

Continuous Cooling Transformations (CCT) diagrams describe exhaustively thermal transformation behaviour of steel; therefore, CCT diagrams valued considering hot prestrain (HPS) conditions is able to describe successfully the thermo-mechanical behaviour of steel. There are several studies that apply the neural network approach to evaluating the CCT diagrams of steels. All the methods use, as input data, the steel chemical composition and the cooling rate and in some cases also the austenization temperature; these method are able to provide as output the starting temperatures of the phase transformations or the material hardness values. The purpose of this study is to provide a forecasting tool that, for a selected steel, is able to supply the thermo-mechanical material behaviours; therefore the selection of the input data to define the neural network model has

been focused on the selection of representative parameters of the thermo-mechanical cycles.

The topological definition of neural model starts from a wide experimental work that planned the carrying out of several hot tensile tests, followed by microhardness and micrographic analyses, aimed to the determination of CCT curves under hot prestrain conditions [15 – 16]. From these studies 112 data useful for training and testing the defined neural network have been extracted. Others data have been selected from literature, finally 155 experimental data have been collected; among them, 115 have been used for training and 40 for testing the selected neural networks [17]. The main results of the experimental campaigns suggested the parameters to select as inputs and outputs of the neural network model. In particular, the factors that influence the phase transformations have been selected as input; six parameters have been considered as influencing parameters: the austenization temperature, the soaking time at the austenization temperature, the prestrain percentage, the prestrain temperature, the strain rate and the cooling rate. The first two parameters have been selected in order to take into account the effect of the prior austenite grain size on the phase transformation; effectively, as suggested by Umemoto and Owen's [18] and Yang and Bhadeshia [19], the phase transformation from the austenite into martensite is strongly associated with the austenite grain boundaries, and therefore the coarsening of the austenite grain promotes the occurrence of diffusive transformations.

As outputs of the neural network, 5 parameters, that are evaluated in all the experimental works, were assigned as the Vickers microhardness, the martensite start temperature (Ms), the Martensite finish temperature (Mf), the percentage of martensite and the percentage of bainite. Hence three different neural networks have been designed; the topology of each of them is depicted in figure 1.

In order to achieve a better readability of the obtained results, the outputs of each neural networks has been post-processed; the linear regression between the network response and the target data allowed to evaluate the fitting capability of model to the experimental data in the training and in the testing phases. The evaluation of the regression coefficient R provided the degree of correlation between the experimental and the foreseen data. In figure 2 and 3 the linear regression analysis for all the output data are displayed. The results evidenced

that the complexity achieved, considering 6 hidden layers, is already enough to describe the system.

In effect no significant predicting capability improvement has been observed considering a higher number of the hidden layers.

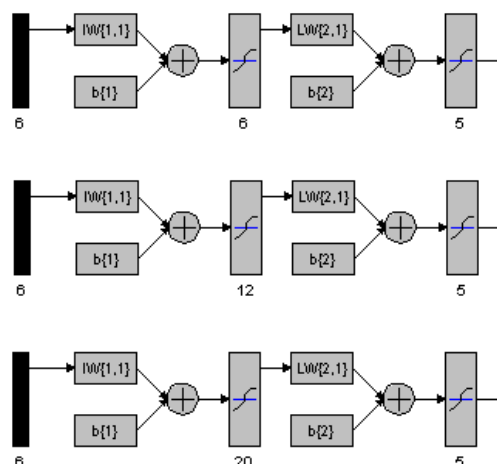


Figure 1. Designed neural networks, 6-6-5, 6-12-5, 6-20-5.

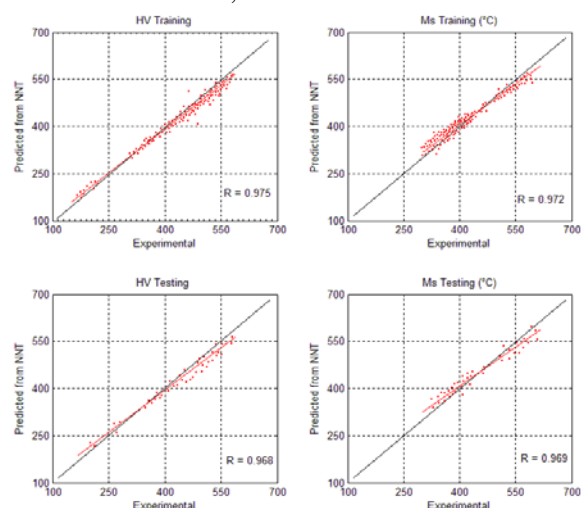


Figure 2. Linear regression between the network response and the target in the training and testing phases. Results for HV, Ms and Mf.

The post-processing of the neural network outputs evidenced a good agreement between the experimental and the foreseen data only for three output parameters: the HV, Mf and Ms values. These parameters reach a correlation coefficient value near to 1. A light decreasing of the R value has been observed in the post-processing of the testing outputs.

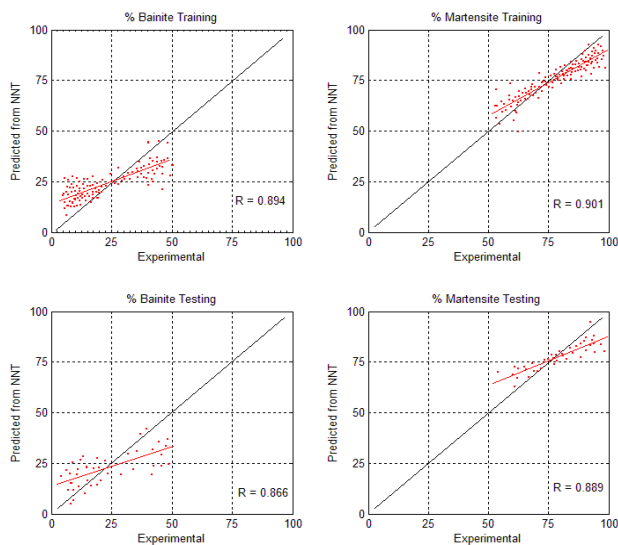


Figure 3. Linear regression between the network response and the target in the training and testing phases. Results for percentage of Bainite and percentage of Martensite.

The small difference between R values for a given parameters indicate a good generalization capability of the neural model. A noisy result was obtained for the output parameters percentage of bainite and percentage of martensite. As shown in figure 3, the correlation between the experimental and the trained data decreased. This results is correlated to the difficult to distinguish and therefore to evaluate the percentage of diffusive phases as bainite, pearlite and ferrite. This difficult rebounds on the prediction accuracy of the percentage of martensite.

4 Conclusions

A model able to predict the hardness and the specific microstructure of 22MnB5 steel as a function of main parameters that are fundamental in hot stamping processes, using a neural network approach with a Bayesian framework, has been designed.

Three different neural networks, with topology 6-6-5, 6-12-5, 6-20-5, have been considered. In order to achieve a better readability of the obtained results, the outputs of each neural networks have been post-processed.

The linear regression between the network response and the target data allowed to evaluate the fitting capability of model to the experimental data in the training and in the testing phases.

The results evidenced that the complexity achieved considering 6 hidden layer is already full enough to describe the system.

A good agreement between the experimental and the foreseen data was found only for three output parameters: the HV, Mf and Ms values.

A noisy result was obtained for the output parameters percentage of bainite and percentage of martensite; this was attributable to the difficult to distinguish and therefore to evaluate the percentage of diffusive phases as bainite, pearlite and ferrite.

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