A Thermography-based Online Control Method for Press Hardening

E. Garcia-Llamas, J. Pujante, P. Torres, F. Bonada

1 Eurecat, Centre Tecnològic de Catalunya, Unit of Metallic and Ceramic Materials, Plaça de la Ciència, Manresa 08243, Spain
2 Eurecat, Centre Tecnològic de Catalunya, Smart Management Systems, Av. Universitat Autònoma, 23, Cerdanyola del Vallès 08290, Spain

E-Mail: *eduard.garcia@eurecat.org

Abstract. The aim of this work is to investigate a simple on-line control methodology applicable to press hardening. Short production runs were performed in a laboratory plant, using a pyrometer to measure sheet and die temperatures with varying processing conditions. Sheets thus treated were studied in terms of microstructure and mechanical properties. Different closing die time and refrigeration conditions were employed to force OK and Not OK conditions. The experimental data including the process variables as well as the resultant temperatures have been analysed and modelled by means of statistical analysis and Machine Learning algorithms, to discover hidden correlations that can lead to actionable predicting models. The results show a direct link of the final temperature with the microstructure and its hardness. The outcome of this paper can be used for efficient process design and detection of anomalous temperature meanwhile an industrial hot stamping process take part. In addition, the analysis performed can help productivity and quality assurance while leading towards a smarter and more efficient manufacturing scenario.

1. Introduction

Press hardening has secured its position as a staple technology for safety cage Body in White applications, offering a very favorable combination of formability and high mechanical properties [1,2]. Press hardening presents a specific challenge: heat treatment of the material is performed during forming part, as opposed to being a property of the raw material. Friction and tool wear [3] and thermal history parameters can affect the efficiency of the whole process and its result [4]. This double requirement of generating complex geometry while performing a final heat treatment, coupled by the typical use in safety cage parts, makes process control and traceability particularly relevant to press hardening. All, while maintaining the current lightweighting trend and an affordable cost.

The advent of Zero-Defect strategies and Industry 4.0 concepts involves process monitoring as tool to generate traceability data, predict OK/NOK production and, potentially, enable feedback loops actively ensuring production quality [5]. Some works in the literature already address its applicability to press hardening; from context and system architecture proposals [6] to actual implementation concepts, such as furnace control in [7]. Due to thermal history playing such an important role [8], temperature monitoring arises in almost all proposals for process control; being relatively non-invasive and easy to implement, use of thermography seems a very adequate strategy. A good summary of capabilities is presented by Sturm [9].

Regardless of the approach in data collecting, analysis seems to befall on Machine Learning algorithms. This analysis strategy allows for autonomous development of control systems, able to adapt
learning from actual production with reduced need for human intervention. Machine learning or artificial intelligence algorithms are able to predict the behavior of complex systems without the need of understanding the real physics, just by learning from the historical data. Inside these algorithms two big groups can be distinguished: supervised and unsupervised. The supervised methods are based in labeled data, where depending if the data is discrete or continuous, a classification or a regression can be used. Here several models like Random Forest [10], Support Vector Machine [11] or Artificial Neural Networks [12] can be used. On the other side, unsupervised methods do not require labeled data. Although these methods are in general less precise than the former ones, are very convenient when the data cannot be labeled and allow to find hidden patterns, anomalies, and different behaviors.

This work showcases a concept for non-invasive on-line control methodology as a reliable quality control set up in press hardening process. Infrared equipment were used to measure the steel sheet and die evolution temperature with different process conditions forcing OK and NOK conditions. The obtained data with all the different process variables were analyzed and modelled by means of statistical analysis and Machine Learning algorithms. The aim of the study is to demonstrate that Machine Learning algorithms can be used to analyze production data obtained from relatively simple sensor setups, producing online quality estimations that can be used for control and traceability, on the one hand, or as a first step in a closed-loop zero-defect system.

2. Experimental methodology

2.1. Press hardening tests

All the material studied in this work was commercial Al-Si coated 22MnB5 sheet steel, 1.7 mm in thickness. In its as-delivered condition it is a cold rolled steel sheet with ferrite-pearlite microstructure and a metallic Al-Si coating approximately 25 µm. Chemical composition is presented in Table 1.

| Material   | C    | Si   | Mn   | Cr   | Al    | Ti    | B     |
|------------|------|------|------|------|-------|-------|-------|
| 22MnB5     | 0.233| 0.235| 1.130| 0.015-0.35 | 0.02-0.06 | 0.02-0.05 | 0.003-0.005 |

The tests were performed at Eurecat semi-industrial hot stamping line; details can be found in [13]. The steel samples were introduced in a convention/radiation horizontal roller furnace (3 meters long) in open (oxygen-containing) atmosphere at 930 °C for 320 seconds. Austenitized blanks were extracted from the furnace and manually transferred for cooling, with transfer time under 5 s. Samples were then quenched in a set of flat, water-cooled dies, under a mean pressure of approximately 25 MPa. These conditions should ensure that cooling rates are in all cases above the critical cooling rate, commonly established in the literature around 35 °C/s [1].

Different production series were performed varying cycle time (time between blanks) and closed die time and allowing the tools to accumulate heat (Table 2, Table 3). The aim of this was to generate conditions which result in a scattering of blank temperatures at the end of the quench.

2.2. Infrared characterization

Initially, three infrared equipment were located at the end of the heat treatment to monitor the correct quenching process. Two pyrometers were used (Optris CTlaser 3M), one for the high temperatures in the range of 250 - 1800 °C (3MH3 Model) and other for low temperature in the range of 50 - 400 °C (3ML Model). A thermographic camera (FLIR A655sc) with a range of temperature from -40 °C until 2000 °C was used for redundancy and to evaluate possible thermal gradients. Figure 1 shows the initial set-up with the three infrared equipment focused on the flat die.

Once validated, the on-line control methodology was setup based on the low temperature pyrometer; as this sensor provided signals for blank temperature at the end of the process and tool temperature. All
signals were obtained in the area corresponding to the center of the blank. This is to avoid temperature irregularities close to the borders of the blank.

![Infrared equipment set-up to check the temperature of the 22MnB5 sheet: A) the pyrometer with the low range temperature (50-400 °C), B) the pyrometer with the high range temperature (250-1800 °C), and C) the thermographic camera with a range temperature from 250 to 1800 °C. In D) is shown the flat water cooled die.]

2.3. Sample analysis
Small samples were cut from the center of the processed sheets, in the approximate point where pyrometer measurements were obtained. Vickers hardness (HV1) and microstructure were studied from these samples.

2.4. Machine Learning
The information available from the experiments, process data and sample analysis, allows to have labeled data and therefore supervised learning can be used. As the output target is continuous (Vickers hardness) regression models are considered.

For the data driven machine learning approach for the hardness prediction, several regressors and ensembles from scikit-learn [14] are considered: Linear Regression (LR), Random Forest Regressor (RFR), Support Vector Regression (SVR), K-Neighbors Regressor (KNR) [15], Gradient Boosting Regressor (GBR) [16], Ada Boost Regressor (ABR) and Extra Trees Regressor (ETR) [17].

From the 59 samples of the full dataset, 80% have been used for training and 20% for test. This proportion has been fixed for all the models and iterations presented in this work. Additionally, 5-fold cross-validation has been used to explore different subsets of training/test sets. Both the prediction accuracy and standard deviation are presented to ensure that the selected models do not suffer from overfitting. Several hyperparameters (such as number of estimators, maximum depth or learning rate for instance) have been tested in order to optimize the algorithm hyperparameters that minimizes the root mean squared error of the prediction. A first exploration of the candidate models using as input variables the die closing time and the sheet temperature and output target hardness was carried out. The better performing models were RFR and ETR. The detailed results are discussed in section 3.

2.5. Dilatometry tests
A TA Instruments DIL805 A/D dilatometer was used to check the results obtain in the semi-industrial line, by generating analysis of quench conditions interrupted inside the martensitic transformation range. Tests were performed on flat samples EDM-cut from the steel sheet.

In a first series of interrupted quench tests, samples were heated up to 930 °C for 320 seconds and cooled down at 50 °C/s until reaching 450, 350, 250 and 150 °C, finally brought to room temperature at a slow cooling rate. Figure 2 A). A second series of tests simulated the stacking of warm steel sheet after fabrication. In this case, temperature was held for 60 seconds upon reaching different temperatures (450, 350, 250 and 150 °C) with final cooling down of 10 °C/s (Figure 2 B).
3. Results

3.1. Press hardening experiments and component hardness
Table 2 shows the press hardening condition applied in the different test and the average hardness. The change in the cycle time (time between stamping sheets) from 40 to 30 seconds, the die closed time and the amount of the sheets; had no effect on the average hardness.

| Serie Nº | Cycle time (seconds) | Die closed time (seconds) | Amount of sheets | Av. Hardness (HV1) |
|----------|----------------------|--------------------------|------------------|--------------------|
| 1        | 40                   | 4                        | 20               | 486 ± 10           |
| 2        | 40                   | 2.5                      | 5                | 484 ± 18           |
| 3        | 30                   | 2.5                      | 15               | 473 ± 22           |

Furthermore, an infrared control of the temperature was performed on all the metal sheets after press hardening by thermographic camera. Average temperature of the steel sheets were analysed in ellipsoid 330 x 112 mm to reach the most reliable information.

As can be seen in Figure 3, despite the different conditions (see Table 2) the same tendency was observed in all the Series: a clear increase of the temperature in the first 6 strokes and then temperature stabilized. In the first stroke the temperature was around 120 ºC and at last stokes the temperature was up to 240 ºC. These results are important to understand the dynamics of the system (water-cooled dies-hot steel sheet) and it is interesting to take in account as a valuable result to evaluate the synergies in industrial process.

Once the system was validated, additional experiments were carried out to find out the limits of the system, generating anomalies that might appear in a malfunction of industrial process, like a hot spot or incorrect time in the die closed time. Cycle time was set to 40 seconds for these tests, and three of them were done without refrigeration and allowing the die to accumulate temperature. The last series, number 7, was done with refrigeration and it was considered as a reference to compare the anomalous values of temperature and hardness. In all these series only one infrared sensor was used, the low temperature range pyrometer. Detailed information can be observed in Table 3.
Figure 3. Average temperature vs Stroke number of three different series. Conditions of the series can be seen in Table 2.

Table 3. Press hardening conditions applied in the cycle time, die closed time, amount of the and whether the die was refrigerated sheets. Moreover, it shows the average hardness of the steel sheets treated.

| Serie Nº | Cycle time (seconds) | Die closed time (seconds) | Amount of sheets | Refrigerate d Die | Av. Hardness (HV1) |
|----------|----------------------|--------------------------|------------------|-------------------|--------------------|
| 4        | 40                   | 1                        | 20               | No                | 341 ± 6            |
| 5        | 40                   | 3                        | 20               | No                | 445 ± 6            |
| 6        | 40                   | 5                        | 10               | No                | 460 ± 5            |
| 7        | 40                   | 5                        | 10               | Yes               | 472 ± 6            |

From Table 3, it can be seen that there is a direct correlation between the die timing and the average hardness obtained. These results show a direct link of the final temperature, which is directly linked with the die closing time, with the microstructure and its hardness.

3.2. Analysis of process data

The data generated and summarized in Table 3 was used to extract the maximum information by machine learning algorithms. Figure 4 shows the temperature profile obtained from the pyrometer. From this data, several metrics related with sheet temperature, die temperature and cycle time are obtained. For parameter a (sheet temperature), the average value of the whole section of the curve has been considered. For the die temperature (section b), several values of the die after removing the sheet are considered.

Figure 4. Temperature profile from the pyrometer corresponding to one cycle.

3.2.1 Statistical analysis

Figure 5 A) presents the hardness as a function of the average sheet final temperature of each sample. The graph shows, as expected, a clear correlation between the sheet temperature at extraction and the
achieved hardness- a drop is particularly noted as temperatures approximate the Ms temperature [1]. This relationship can be modelled with a quadratic equation (Equation 1). The dashed line from Figure 5 represents the quadratic fit corresponding to the next equation:

\[
D = 472 \text{ HV1}; \quad T < 260 ^\circ\text{C} \\
D = -0.004 \cdot T^2 + 2.2105 \cdot T + 166.95; \quad T > 260 ^\circ\text{C} \quad \text{Equation 1}
\]

The previous equation provides a prediction of the hardness for each sample as function of the sheet temperature with an average relative error of 4.21 % and a standard deviation of 4.66 %.

On the other hand, Figure 5 B) presents the calculated cooling rate for each sample, showing that all sheets with low hardness had experienced cooling well above the critical colling rate. This indicates that all these samples could have been turned into an OK component if a decision of increasing closed die time could have been implemented in real time.

3.2.2 Analysis with Machine Learning methods

To improve the prediction provided by the quadratic function, a machine learning based approach is presented. A fist analysis of the Pearson correlation of several factors with the final hardness [18] shown that the features that better correlate with the final hardness are the die closing time and the sheet temperature. On the contrary, the die temperature and the time of the plateau (i.e., time duration of section a in Figure 4) have lower correlation.

A first iteration done with the best performer RFR and the ETR models, showed a relative error of 3.73 % and 4.48 % respectively. This analysis was repeated with the same algorithms but including all the available variables, including the rest of features with a lower linear correlation. For this scenario, the predictions have been further improved with a relative error of 3.39 % for the RFR and 3.17 % for the ETR. Notice that the relative error has decreased for both models. This means that although the die temperature and the time of the plateau alone does not give a good linear correlation with the target variable, they provide valuable information when are included together as input variables for those algorithms or learners that can consider non-linear relationships.

Finally, the RFR and the ETR have been used to predict the hardness of the samples without considering the final sheet temperature. These predictions have provided a relative error of 4.47 % for the RFR and 4.74 % for the ETR. The relative error found for all the other trained models are slightly higher than for the RFR and ETR, around 1 % or less in all the cases (Table 4).

By comparing results in Table 4, it can be noticed that the machine learning algorithms improve the results in three of the six cases. In this comparison it has to be considered that in the polynomial fit all
the data is used to obtain the equation and to calculate the error, while in the machine learning algorithms only 80 % of the data is used for the training and 20 % to calculate the error.

Table 4. Error and standard deviation obtained with the different prediction strategies [%]

| Inputs                          | Conventional Regression | Random Forest Regressor | Extra Trees Regressor |
|---------------------------------|-------------------------|-------------------------|-----------------------|
| Closed die time and sheet temp. | 4,21 (4,66)             | 3,73 (3,79)             | 4,48 (4,48)           |
| All variables                   | 3,39 (3,79)             | 3,17 (4,18)             |                       |
| All excluding sheet temperature | 4,47 (5,36)             | 4,74 (5,52)             |                       |

These results show that the machine learning-based algorithms have been able to provide a better prediction than the conventional statistics methods. Moreover, machine learning has proven to be capable of predicting hardness without using final sheet temperature, thus proving that it is possible to foresee a quality parameter before the forming cycle ends, and therefore a correction strategy (e.g., increasing closed die time) could be implemented as a feedback loop.

3.3. Dilatometry tests

Figure 6 shows the hardness values obtained following the conditions defined in Figure 2). In Figure 6 A), the hardness values obtained correlates with the hardness in the experimental tests in the semi-industrial line. The sample quenched at 450 ºC had the lowest hardness value of 412 HV1, meanwhile the highest value (469 HV1) is on the sample quenched at 150 ºC. These values match with the close die time of 1 second and 5 second of the experimental test in the semi-industrial line (see Table 3). Figure 6 B) shows the hardness values with a holding time of 60 seconds at three different temperature, 100 ºC, 150 ºC and 250 ºC to reproduce the reheating of the stack of the steel sheets at different temperatures. A negative impact in the hardness values when the holding temperature increased can be seen. This effect is not neglectable and it might compromise its microstructure and the reliability of the final part.

4. Summary and Conclusions

In this work, a simplified quality control method for press hardening has been demonstrated in a simplified environment. The aim of this was to provide a means of quality prediction and, if possible, evaluate the suitability of this method for process control. The main points observed are the following:

• Production conditions could be forced in which blanks were extracted from the die at elevated temperatures, but keeping cooling rate above the acceptable levels; i.e., processes where dynamic adjustment of die closing time could have resulted in satisfactory cooling.
In this condition, component hardness could be linked to final sheet temperature, both through statistical regression and through analysis based on Machine Learning methods.

Moreover, machine learning methods were able to foresee production quality without an actual measurement of final blank temperature.

Dilatometer tests have been a valid method to reproduce semi-industrial conditions.

Despite the simplified environment and modest amount of tests performed, these results show that this control methodology could be realistically applied to press hardening as a predictor for non-OK parts. This algorithm could therefore be expanded into a system able to dynamically adjust production parameters (i.e. dwell time, cycle time) to ensure successful production.

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