Development of a soft sensor for determining the cooling rate for press hardening of medium manganese steel

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Abstract. Press-hardened ultra-high strength steel parts are extensively used in the automotive industry for their lightweight and safety benefits. Medium Manganese Steels offer further advantages due to their high strength and ductility, achieved through a multi-phase microstructure at lower annealing temperatures. However, their industrial application faces challenges due to stricter process control requirements. Data-driven approaches based on process parameters hold promise for advancing material-specific process development. This study establishes a digital material shadow to predict the influence of process parameters on final material mechanical properties. For this aim, a soft sensor is introduced to determine the crucial parameters, particularly cooling rate and forming temperature during press hardening, leveraging the measurement of tool temperature data. Linear regression is applied to correlate tool temperature increases with cooling rates and final temperatures. Comparisons of the soft sensor predictions with finite element simulations demonstrate high accuracy, with deviations below 1 %. The proposed soft sensor enhances the precision of data-driven predictions for final material properties, supporting the integration of Medium Manganese Steels into press-hardened applications while enabling sustainable manufacturing practices.

Keywords: Digital Shadow; Press Hardening; Medium Manganese Steel; Soft Sensor

1 Introduction

The increasing demand for high-strength steel components in the automotive industry is primarily driven by the dual objectives of enhancing passenger safety and reducing vehicle weight, thereby decreasing overall energy consumption. Medium-Manganese Steel (MMnS) alloys are currently under investigation as a potential alternative to boron-manganese steels, such as 22MnB5, for crash-relevant applications. This interest is due to MMnS alloys' favourable combination of high strength and ductility, which improves crash performance. Additionally, these mechanical properties can be achieved at lower annealing temperatures compared to boron-manganese steels, leading to reduced energy consumption during production.

However, the multi-phase microstructure that enables these advantageous properties necessitates stringent process control, which in turn increases production costs. To facilitate the widespread industrial adoption of MMnS for press-hardened components, a data-driven methodology, grounded in a comprehensive understanding of process parameters and their influence on final material properties, could significantly accelerate implementation. A critical aspect of this approach is the aggregation of all relevant production data into a digital material shadow (DMS) specific to each manufactured component.

Previous research [1] introduced a framework for establishing a DMS in the production of press-hardened MMnS components. However, in practical application, the predictive accuracy of a linear regression model for estimating the final hardness of the press-hardened parts proved insufficient. Two key influencing factors — the cooling rate during press hardening and specimen temperature after forming — could not be directly measured, limiting the model's predictive capability.

This study presents the development of a soft sensor for real-time estimation of the cooling rate and post-forming temperature by monitoring variations in tool temperature during the press-hardening process. A finite element model (FEM) of the press-hardening process is developed to generate a comprehensive database, correlating measured tool temperature changes with the cooling rate and post-forming temperature of the specimen. The proposed method achieves a prediction accuracy of less than 1% for the target parameters, with a computation time below 0.5 seconds. The implementation of this soft sensor provides previously unavailable data, enhancing the feature set utilized for constructing a robust DMS for press-hardened MMnS components.

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2 State of the Art

2.1 Press Hardening of Medium Manganese Steels

Medium-Manganese Steels (MMnS) have emerged as promising materials for body-in-white applications, particularly due to their potential to enhance crashworthiness [2]. This is attributed to their unique combination of high tensile strength and exceptional ductility, which contributes to improved passenger safety [3]. Furthermore, MMnS offer the advantage of reduced energy consumption during production, primarily owing to their lower austenitization temperature compared to conventional boron-manganese steels [4].

The superior mechanical properties of MMnS stem from their fine-grained, multi-phase microstructure consisting of retained austenite, tempered and fresh martensite. However, achieving this microstructural refinement often requires complex multi-step heat treatment processes, such as Quench and Partitioning (Q&P) [5]. The successful implementation of these treatments necessitates precise control over critical parameters, including soaking durations, tool temperatures, and cooling rates during quenching [6].

Studies investigating the influence of hot and cold rolling, followed by annealing, have demonstrated a significant impact on the morphology of retained austenite and the resulting mechanical properties [7].

2.2 Digital Material Twin and Shadow

Over the past several years, digitalization concepts and data-driven methodologies have been extensively applied to optimize production processes. Two distinct approaches have recently emerged in this context: the digital twin and the digital shadow [8]. While these concepts have been the focus of numerous academic studies, they are often used interchangeably despite their fundamental differences [9].

In the domain of manufacturing technology, digital twins and digital shadows are both utilized to represent physical assets. However, a digital shadow captures only a specific aspect by aggregating and reducing data, whereas a digital twin is a comprehensive virtual representation of a physical asset that is continuously updated [10]. Digital shadows are tailored to facilitate real-time decision-making within specific operational domains, and multiple digital shadows can exist for a single physical asset [11].

This study investigates the experimental processing of newly developed materials in metal forming operations. In the field of materials science, specific digital twin and digital shadow concepts have been introduced to enhance material innovation and process optimization. For instance, multi-scale digital twin frameworks have been proposed to accelerate advancements in materials science [12], while digital material shadows have been developed to capture and visualize key material characteristics throughout the production chain [13]. Building on these principles, further advancements have been made in implementing digital material shadows in the press hardening of medium-manganese steels [14]. A framework to create a DMS for the process chain of press hardening of MMnS was proposed, enabling the prediction of product properties based on process data. However, since critical parameters such as cooling rate during press hardening and the post-forming specimen temperature could not be measured, the prediction accuracy on the resulting hardness was not satisfactory with an R^2-value of 0.27 [1].

2.3 Soft Sensor in press hardening

A soft sensor is a computational model or algorithm designed to enable indirect measurements of process variables that are difficult to access directly. This is achieved by collecting easily measurable data and parameters, which are then used to compute the desired target variable [15].

Martschin et. Al [16] present the development of soft sensors for property-controlled multi-stage press hardening of 22MnB5 steel. A temperature soft sensor, based on Dynamic Mode Decomposition combined with a Kalman filter, enables real-time estimation of temperature distribution with an error below 10°C. Additionally, an artificial neural network-based microstructure soft sensor predicts the final phase composition with an average deviation of 1.8%, allowing for in-situ property control and optimization of the press hardening process. However, this soft sensor uses spring loaded thermocouples directly measuring the temperature during the press hardening process. This thermocouple placement risks the failure of sensitive thermocouples due to relative movement of the specimen and tool. Thus, positioning the thermocouples inside the tool, the risk of failure can be reduced.

3 Press Hardening Process and Modelling

The press hardening process is integrated with a defined heat treatment according to the Quenching and Partitioning (Q&P) principle. Initially, cold-rolled blanks are cut into square dimensions of 130 x 130 mm² and subjected to austenitization in a radiation furnace at 850 °C for ten minutes. Subsequently, they are manually inserted into a Lauffer deep drawing press. The total transfer time of approximately six seconds results from the manual transfer from furnace into the tool and the die closing. The depth of the deep-drawing process is consistently maintained at 16.2 mm. To influence the cooling process after forming, a heated press hardening tool is employed, with tool temperatures individually set to 120°C, 150°C, and 180°C respectively.

Following the forming process, the components undergo die quenching for 30 seconds within the closed tool before being manually transferred to a convection oven set at 400°C for five minutes. During hot stamping and die quenching, tool temperature is continuously monitored using six thermocouples. These thermocouples are positioned at a distance of 2.5 mm

from the surface of the die in three distinct locations on each arm of the cross-die as shown in Fig. 1. a).

The initial specimen temperature is calculated using the heat transport equation (1) and is set to $T_i = 710$ °C.

$$T_i = e^{-(Bi*Fo)} * \left(T_{surface} - T_\infty\right) + T_\infty \qquad (1)$$

A thermomechanical finite element (FE) model is developed using Abaqus to simulate the press hardening processes of a cross-die specimen, see Fig. 1. b). The model consists of four main components: a blank, a die, a holder, and a punch, all meshed with elements type C3D4T. The blank is defined as a deformable body, while the other components are modelled as rigid bodies to reduce computational complexity. The material properties of the blank and the forming tools are incorporated based on experimental data.

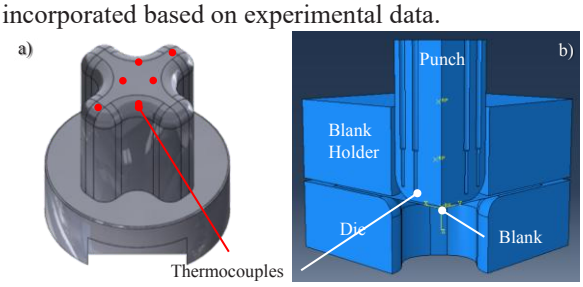


Fig. 1. a) Positions of thermocouples in the punch b) FE model setup

The simulation process is divided into two stages: the forming step, where the blank is pressed into shape, and the subsequent cooling phase. A coupled temperature-displacement analysis is employed to capture both thermal and mechanical interactions. The boundary conditions include initial temperatures of 710°C for the blank and varying tool temperatures of 120°C, 150°C, and 180°C respectively. Heat transfer between the blank and the punch is modelled using an interfacial heat transfer coefficient (IHTC) of $\alpha = 5.15\ \frac{kW}{m^2K}$, which is determined by means of inverse modelling, comparing the simulation results with experimental temperature measurements from thermocouples embedded in the forming tool. The results are displayed in Fig. 2.

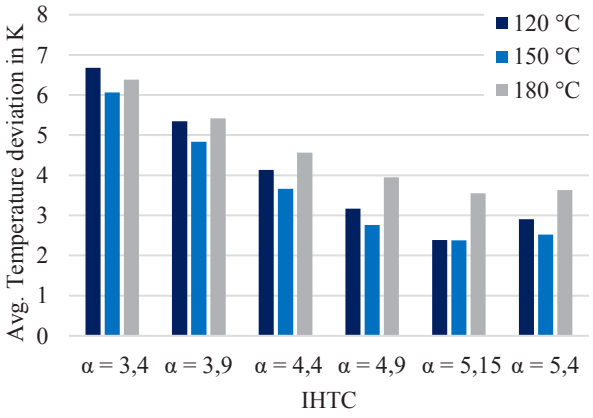


Fig. 2. Average temperature deviation comparaison for different tool temperatures and IHTCs

A sensitivity analysis is conducted to evaluate the impact of different parameters, such as IHTC and tool temperature, on cooling behaviour. The results indicate that variations in IHTC significantly influence the temperature evolution of the blank, whereas the impact of air gaps as shown in Fig.3 formed during the process is negligible.

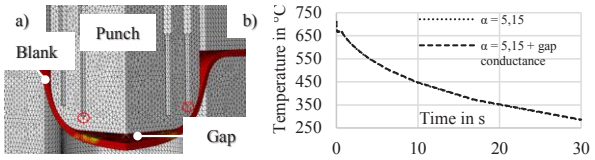


Fig. 3. a) air gap between punch and blank b) influence of gap conductance on the blanks cooling rate

4 Temperature prediction using Soft Sensor

Using the FE simulations, a dataset is then created by varying initial specimen temperature between 850 and 600 °C in steps of 50 K and tool temperature between 120 and 180 °C in steps of 10 K. A data set is created by extracting features from the time-temperature curve at the position of the thermocouples. The extracted features – maximum temperature, maximum temperature increase and final temperature (see Fig. 4.) represent the characteristics of the punch's temperature change.

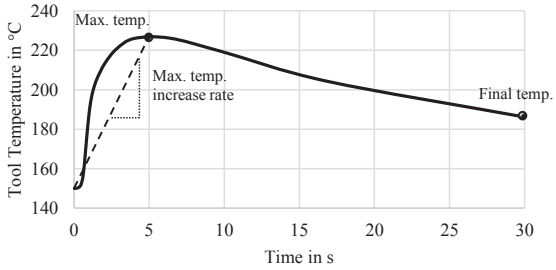


Fig. 4. Measured tool temperature curve and extracted features

The developed dataset from FE simulations serves as the training data for the soft sensor algorithm. This algorithm is designed to correlate tool temperature measurements with the cooling rate of the blank using Matlabs classification learner. The developed soft sensor is then tested with parameter combinations that were not part of the training data set. The predicted target parameters cooling rate, final blank temperature and initial blank temperature are then being compared to the simulation results. Table 1 shows the results for three different tool temperatures and blank temperatures, not used in the training data. In the first case, an initial tool temperature of 140 °C and blank temperature of 830 °C is chosen. Using the soft sensor, the predicted of the initial blank temperature is deviation by 0.014 %. The prediction accuracy of the cooling rate in this case is 99.25 %, leading to a prediction deviation in the final specimen temperature of 1.22 %. The overall prediction of the cooling rate is accurate with a deviation lower than 1 % with similar accurate predictions for the final and initial blank temperatures.

Table 1. Comparison of predicted target parameters vs. simulation results

Simulation no.	1	2	3
Initial tool temperature	140 °C	155 °C	165 °C
Initial blank temperature	830 °C	715 °C	645 °C
Predicted initial blank temperature	830.114 °C	715.095 °C	644.912 °C
Deviation initial blank temperature	0.014 %	0.013 %	0.013 %
Predicted cooling rate	17.055 K/s	13.592 K/s	12.055 K/s
Actual cooling rate	17.184 K/s	13.588 K/s	12.141 K/S
Deviation cooling rate	0.75 %	0.29 %	0.71 %
Predicted final temperature	318.35 °C	307.24 °C	283.35 °C
Actual final temperature	314.48 °C	307.36 °C	280.77 °C
Deviation final temperature	1.22 %	0.04 %	0.91 %

5 Conclusions

The presented method facilitates the integration of cooling rate data and initial and post-forming blank temperatures during press hardening into the DMS framework developed in previous work. By continuously monitoring tool temperature throughout the press hardening process, this method utilizes the data to predict parameters that cannot be directly measured but significantly influence the final product properties in MMnS press hardening. This enables a more accurate prediction of the actual material properties of the final product, enhancing understanding of how deviations in process parameters affect production outcomes. Consequently, it holds potential for improving the industrial application of MMnS press-hardened components.

The use of a trained statistical model allows for accurate prediction of target parameters in under 0.5 seconds, enabling real-time production monitoring. However, the accuracy of this method has only been tested against synthetic data using FE simulations. The ability to predict target parameters for actual processes primarily depends on the accuracy of the FE model employed. Additionally, this method does not provide local heat distribution details as FE simulations do. Therefore, real-world accuracy needs to be validated before implementing this soft sensor into a DMS pipeline. Once validated with real data, the soft sensor can offer realistic process input data for applications such as microstructure simulations, thereby increasing understanding of interactions between process parameters and material behaviour throughout the process chain.

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References

1. K. J. Tilly, C. Idzik, and D. Bailly, IOP Conf. Ser.: Mater. Sci. Eng. **1307**, 1 (2024).
2. J.-H. Schmitt and T. Iung, Comptes Rendus Physique **19**, 8 (2018).
3. D. Rosenstock, J. Banik, T. Gerber, and S. Myslowicki, IOP Conf. Ser.: Mater. Sci. Eng. **651**, 1 (2019).
4. C. Tong, Q. Rong, V. A. Yardley, X. Li, J. Luo, G. Zhu, and Z. Shi, Metals **10**, 12 (2020).
5. B. de Cooman and J. Speer, steel research int. **77**, 9-10 (2006).
6. C. Blankart, R. Emmrich, L. Bähren, and U. Krupp, steel research int. (2023).
7. G. Mishra, A. K. Chandan, and S. Kundu, Materials Science and Engineering: A **701** (2017).
8. S. M. E. Sepasgozar, Buildings **11**, 4 (2021).
9. T. Bergs, S. Gierlings, T. Auerbach, A. Klink, D. Schraknepper, and T. Augspurger, Procedia CIRP **101** (2021).
10. G. Zhou, C. Zhang, Z. Li, K. Ding, and C. Wang, International Journal of Production Research **58**, 4 (2020).
11. *Interdisciplinary Excellence Accelerator Series*: *Internet of Production*, Ed. by C. Brecher, G. Schuh, W. van der Aalst, M. Jarke, F. T. Piller, and M. Padberg (Springer International Publishing, Cham, 2023).
12. S. R. Kalidindi, M. Buzzy, B. L. Boyce, and R. Dingreville, Front. Mater. **9** (2022).
13. J. Wang, S. Wesselmecking, U. Krupp, and M. Ackermann, *Data Guided Materials Processing - Digital Material Twin and Digital Material Shadow* (2022).
14. S. Wesselmecking, M. Ackermann, C. Blankart, J. Wang, F. Brasche, T. Plum, S. Qin, F. Pütz, S. Münstermann, C. Broeckmann, G. Hirt, and K. Ulrich, in *Interdisciplinary Excellence Accelerator Series*: *Internet of Production*, Ed. by C. Brecher, G. Schuh, W. van der Aalst, M. Jarke, F. T. Piller, and M. Padberg, 1–16 (Springer International Publishing, Cham, 2023).
15. L. Fortuna, S. Graziani, A. Rizzo, and M. G. Xibilia, *Soft Sensors for Monitoring and Control of Industrial Processes* (Springer London, London, 2007).
16. J. Martschin, M. Wrobel, J. Grodotzki, T. Meurer, and A. E. Tekkaya, Automot. Innov. **6**, 3 (2023).