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Development of a digital material shadow for the press hardening route of medium manganese steel

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Abstract. Press-hardened ultra-high strength steel parts are widely used in the automotive sector for their lightweight and safety advantages. Medium-Manganese Steels (MMnS) are being explored as an alternative to boron-manganese steels due to their high strength and ductility after quenching, achieved at lower annealing temperatures thus reducing energy usage and carbon emissions. However, industrial adoption of MMnS is hindered by challenging processing requirements, e.g. in cold-rolling and press hardening.
To expedite and improve the process development, data-driven decisions based on process parameters hold promise. Establishing a link between process data and the final produced part necessitates the development of a framework for a Digital Material Shadow (DMS).
This paper investigates the development of a DMS framework for the cold rolling and press hardening process chain. In conjunction with conventional data acquisition methods employed for cold rolling, novel data acquisition techniques are introduced specifically tailored for press hardening, ensuring the comprehensive availability of relevant data. Moreover, a data pipeline is implemented to enable automatic processing, visualization, and analysis of process data. To facilitate seamless data linkage across processes in the DMS, an ID-system is introduced. Finally, the developed framework's validity is demonstrated by creating a DMS for press-hardened MMnS parts, showcasing its potential for practical applications.

1. Introduction

The increasing use of advanced high strength steel parts in the automotive industry is driven by the objective of vehicle weight reduction in order to reduce energy consumption and further improve passive passenger safety. Currently, Medium-Manganese Steels (MMnS) are being examined as a potential alternative to boron manganese steels, such as Mn22B5, for body-in-white applications. MMnS are an appealing option as they offer a combination of high strength and ductility. Remarkably, these properties are achieved at lower annealing temperatures compared to conventional boron manganese steels, reducing energy consumption and CO2 emissions. However, due to the high cost of processing, MMnS faces barriers to widespread industrial adoption. These challenges, particularly in processes such as cold rolling and press hardening, have impeded the smooth integration of MMnS into the manufacturing sector. A data-driven approach, based on a thorough understanding of how process parameters affect material and final product properties, appears to be a promising solution to accelerate the development of MMnS processing by press hardening. Central to this approach is the need to establish a strong link between process data and the final properties of the produced parts. This requires the development of a

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framework for a Digital Material Shadow (DMS). DMS contain reduced, aggregated data to address specific material issues. The initial step is to implement a tracking system to match process data along the process chain with the resulting parts. Next, a data pipeline that collects, processes and aggregates all data from all processes across the process chain, allowing for real-time decision support.

This paper aims to establish these two steps towards a framework for DMS for the press hardening process chain. For this, an ID system is introduced which allows material tracking along the process chain, so that the entire production history of an individual press-hardened component is available. The process data is cleaned, processed and aggregated using an implemented data pipeline which allows detailed analyses and predictions in real time. This is illustrated in this paper by the prediction of the final hardness of the press-hardened part and the occurrence of cracks with the help of process data.

2. State of the Art

2.1. Processing of Medium Manganese Steels

The utilization of Medium-Manganese Steels (MMnS) in body-in-white applications represents a promising avenue, particularly in the context of crash-worthiness. This is attributable to their unique combination of high tensile strength and exceptional ductility, which underlines their potential to enhance automotive safety [1]. Additionally, MMnS holds the prospect of reducing energy consumption during production, primarily due to their lower austenization temperature in comparison to conventional boron-manganese steels [2]. These advantageous mechanical properties are rooted in the intricate fine-grained multi-phase microstructure inherent to MMnS. However, achieving this microstructure often necessitates the implementation of complex multi-step heat treatment procedures, such as Quench and Partitioning (Q&P) [3]. Consequently, this adds a layer of complexity and required precision to the processing of MMnS, especially concerning aspects like soaking times, tool temperature and cooling rates during the quenching process [4].

Mishra et al. [5] looked into the effect of hot- and cold rolling with subsequent annealing on the austenite morphology and mechanical properties of the material. The cold rolling route showed a recrystallized microstructure which leads to yield point elongation, suggesting that hot – and cold rolling parameters have a significant influence on the final mechanical properties and microstructure.

2.2. Digital Material Twin and Shadow

For several years, digitalization concepts and data-driven methods have been extensively utilized to enhance production processes. Two distinct concepts have recently surfaced in this regard: the digital twin and the digital shadow. These topics have been the subject of numerous academic publications. Nevertheless, digital twin and shadow are often used interchangeably [6]. Bergs et al. [7] present detailed definitions of both concepts in the context of manufacturing technology. The authors state that digital twins and digital shadows exist for physical assets. However, a digital shadow reflects only one specific aspect as it is an assignment of reduced and aggregated data, whereas a digital twin is a virtual representation of a physical asset that is consistently updated [8]. Digital shadows are customised to support real-time decision-making in specific domains. Unlike digital twins, there may be several digital shadows for a single physical asset [9].

This paper focuses on the experimental processing of newly developed materials throughout metal forming processes. Specific concepts for digital twins and shadows for materials science have also been introduced in the literature. For example, Kalidindi et al. [10] proposed a multi-scale concept for a digital twin for materials that aims to accelerate the innovation in materials science. Wang et al. [11] have defined a digital material shadow, which can capture and display the pivotal characteristics of the material within a production chain. Based on that, Wesselmecking et al. [12] further developed the concept and implemented it in the press hardening of medium manganese steel. However, their emphasis lies primarily on the digitalization of press hardening tools. Additionally, their analysis is focused to the press hardening alone, without considering the preceding rolling processes that influence the material.

2.3. Data Processing

As previously stated, the focus of this paper is on the collection and analysis of data in the area of cold rolling as well as press hardening and correlate the process parameters with the resulting product quality, in this use case represented by the final hardness. With increasing quality requirements and digital advances, there has been a growing number of publications related to data analysis for forming technology, particularly focusing on hot and cold rolling. Most publications address quality issues that current models cannot explain sufficiently, or non-linear relationships that lack complete understanding. The primary aim of data processing and analysis is to identify relevant parameters and influences [13].

The typical steps for data processing and analysis are data collection, storage, data integration and transformation as well as cleaning, feature selection and finally extracting knowledge by applying classification or regression approaches [14]. One early example of data analysis in cold rolling is the work by Wu et al. [15] who employed data analysis for refining rolling parameters. In their multivariable data analysis for cold rolling, Takami et al. [16] found, that the incoming and outgoing thicknesses, forces, back and forward tension, coil speed at entry and exit, flatness in the middle and at the edges of strips, eccentricity and roll gap positions are the most relevant measurable rolling parameters. Besides that, the authors found that also differences in the material properties and possible introduced damage during the hot rolling processes influences the final product quality.

In the context of press hardening, ascertaining the cooling rate during the process presents a multifaceted challenge due to the unavailability of direct temperature measurements through conventional means. In industrial applications, process monitoring conventionally involves temperature measurements taken on the sheet before and after pressing, as well as monitoring the sheet's placement within the press. In response to this challenge within a multi-step press hardening process, Martschin et al. have introduced a soft sensor utilizing dynamic mode decomposition as a methodology for estimating temperature distribution [17]. Conversely, Li et al. have proposed an alternative approach by determining the interfacial heat transfer coefficient through indirect measurement using a purpose-built testing apparatus equipped with an infrared thermometer and interface pressure sensor [18]. The employment of indirect temperature measurements assumes significant importance in order to facilitate the identification and analysis of essential heat transfer dynamics during the press hardening process.

This brief literature review highlights the critical importance of data processing and analysis in meeting current and future challenges. However, it is noticeable that most of the work done so far focuses on only one process. Data from several processes are rarely processed and analysed together. Specifically, for the press hardening route, a DMS is not yet introduced.

3. Materials and Methods

This chapter describes the material and the processes in more detail. The process chain of interest, including its parameters and measurements, shown in Figure 1. At the beginning, a square-sectioned MMnS billet of 100 mm is cast. Chemically analyzed results of the billet are provided in Table 1, obtained from a sample taken after casting. Following this, the billet is heated to 1200 °C and hot rolled to a 3 mm thickness. To ascertain the effect of process variations on material properties during cold rolling and to allow for experimental processing, the slabs were split into several shorter sheets.

Table 1. Chemical Composition of used alloy.

Fe	C	Mn	Si	Al	Cr	P	S	N
bal.	0.30	4.99	1.55	0.004	0.04	0.005	0.003	0.004

Next, all of the hot-rolled sheets were annealed for a duration of 2 hours at a temperature of 600 °C. This intermediate annealing between hot and cold rolling is essential due to martensite phase of the material and formation of carbides in the material. Otherwise, there is a significant possibility that material failure may result due to the occurrence of cracking during cold rolling. The parameters for annealing were determined on the basis of previous cold rolling trials.

	Cold rolling	Austenitization	Press hardening	Partitioning
Process-parameters	Height-reduction Pass number	Temperature Time	Drawing depth Blankholder force Tool temperature	Temperature Time
Measured data	Force, Torque Rolling speed Hardness	-	Force Displacement Temperature	Hardness

Figure 1. Process chain and its used parameters as well as measured data.

After annealing, the material is descaled and cold rolled in 4 passes from 3 mm to about 1.5 mm using a cold rolling mill with a quarto setup. During cold rolling the force, torque and the rolling speed are measured. In addition, the sheet thickness is measured manually at several points after each pass as well as the hardness (HV1) of the cold rolled sheets is determined.

The final stage of the process chain is the press hardening which needs a defined heat treatment before and after the process, following the Q&P principle. In order to achieve this, the sheets were initially cut into the desired shape. These sheets were then austenitization heat treated in a radiation furnace at 850°C for ten minutes and manually inserted into a Lauffer deep drawing press. The depth of the deep-drawing process remained steady at 16.2 mm. To affect the cooling process following formation, a heated press hardening tool was used, which was separately adjusted to tool temperatures of 120°C, 150°C, and 180°C. After forming, the parts were die-quenched for 30 seconds in the closed tool and manually transferred into a convection oven at 400 °C for 5 minutes. The tool temperature during hot stamping and die quenching was continuously measured by 6 thermocouples. The thermocouples are installed with a 2.5 mm distance to the surface of the die in 3 different positions on each arm of the cross-die, see Figure 2. The final hardness (HV1) was subsequently measured after the specimens cooled to room temperature.

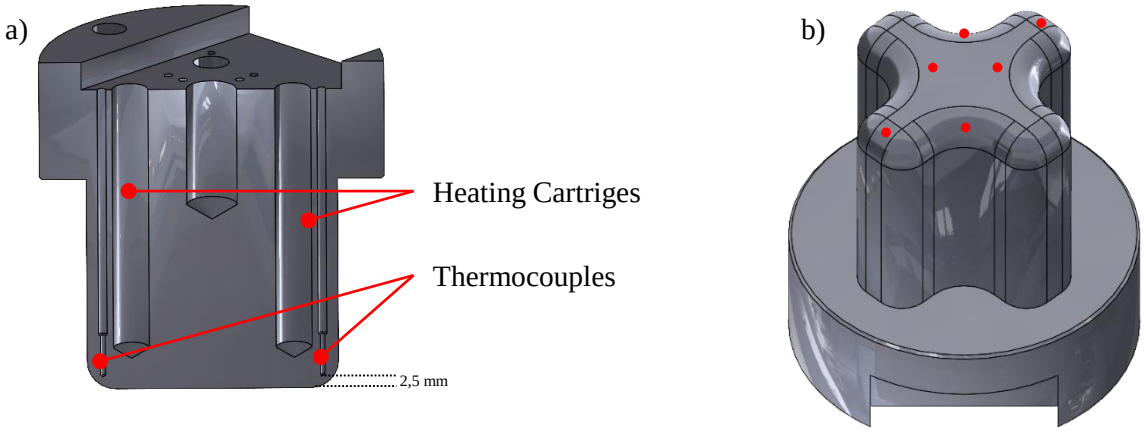


Figure 2. a) Sectional view of used hot-stamping tool b) temperature measurement positions.

4. Results

This chapter outlines the implemented initial steps to develop a framework for DMS. First, an ID system is described, which automates the aggregation of process data from the process chain onto a single sheet that pertains to the final press-hardened part. Following this, the implemented data pipeline is described, and the outcomes are presented, scrutinized, and assessed. Finally, an exemplary demonstration of the potential of the presented approach through the application of regression and classification is shown.

4.1. ID System

In order to automatically match the process data from cold rolling with the data from the press hardening process a simple but informative ID system was established. The ID system consists of several digits that are clearly assigned to a certain characteristic/feature. These features are especially applicable to the manufacturing process and pertain on the one hand to the semi-finished product and on the other hand to the finished part. It consists of the chemical composition, the number of the hot rolled slab, an index for the initial geometry and sheet number for the semi-finished sheet. For the finished product, an additional number for the press-hardened part is added and one number depending on the applied final heat treatment. Figure 3 shows the structure of the developed ID system.

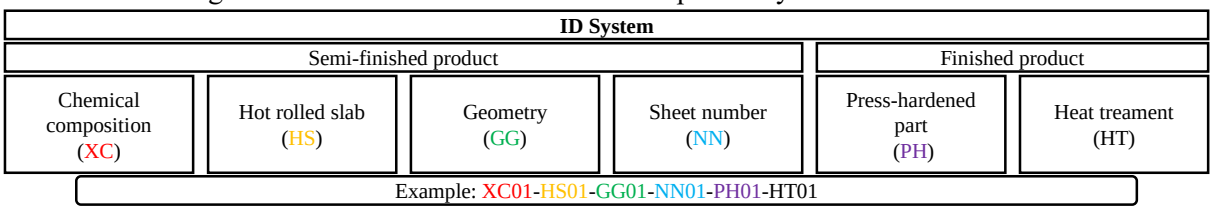


Figure 3. Structure of the ID-System

4.2. Workflow of the data pipeline

Next, automatic data processing is described and explained. As mentioned in the previous chapter, typical data processing consists of the following steps: Data collection, data cleaning/preparation, data processing, visualization and the final data analysis. These procedures were employed for cold rolling and press hardening using Python. Figure 4 shows the steps detailed for cold rolling and press hardening. In contrast to many other publications, the data analysis is not limited to one separate processes, but combines the data from several processes, thus allowing correlations between process parameters and the resulting material properties of a preceding process on the final product properties.

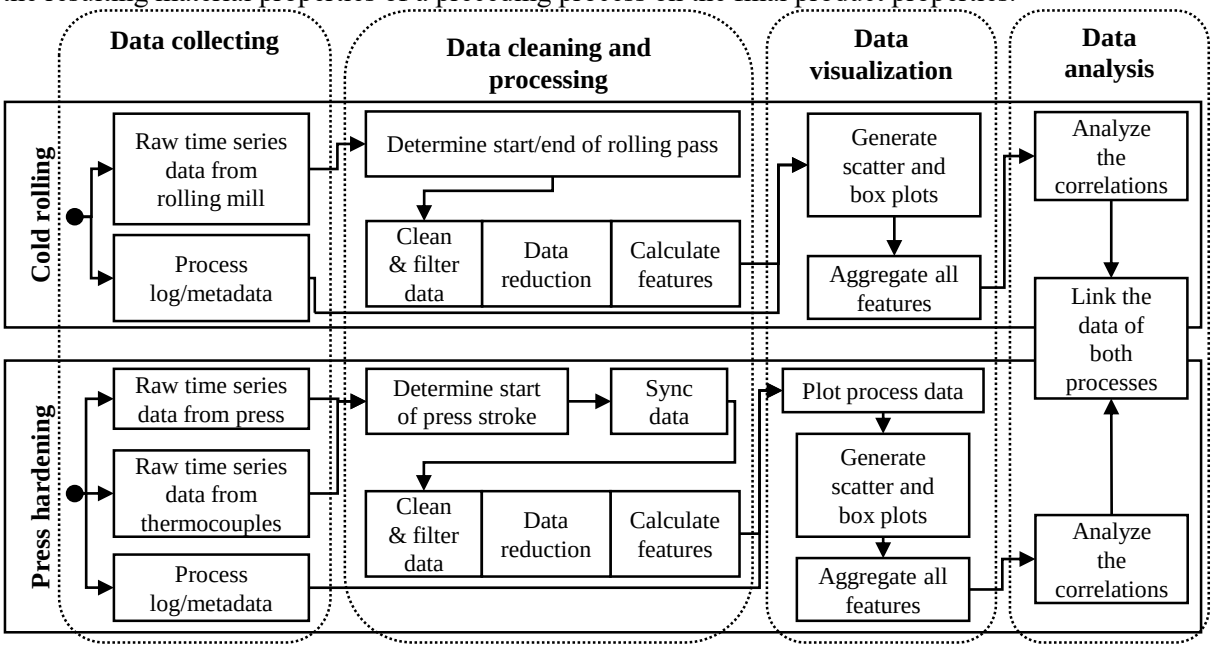


Figure 4. Workflow of the developed data pipeline for cold rolling and press hardening process.

For both cold rolling and press hardening, the fundamental steps in the implemented data pipeline are the same. Data is initially collected, followed by automatic determination of the start and end of the processes, in order to isolate relevant process data. An illustrative example of such process data is provided in Figure 5 a, for the cold rolling process. Next, outliers and measurement errors are eliminated from the process data. Then, the time series data is reduced by calculating features such as the mean

rolling force. These features are saved alongside the time-series data for comprehensive analysis and are used to automatically generate plots for the entire trial. Figure 5 b demonstrates further analysis, showcasing the mean rolling force of each cold rolled sheet in the trial plotted as a box plot.

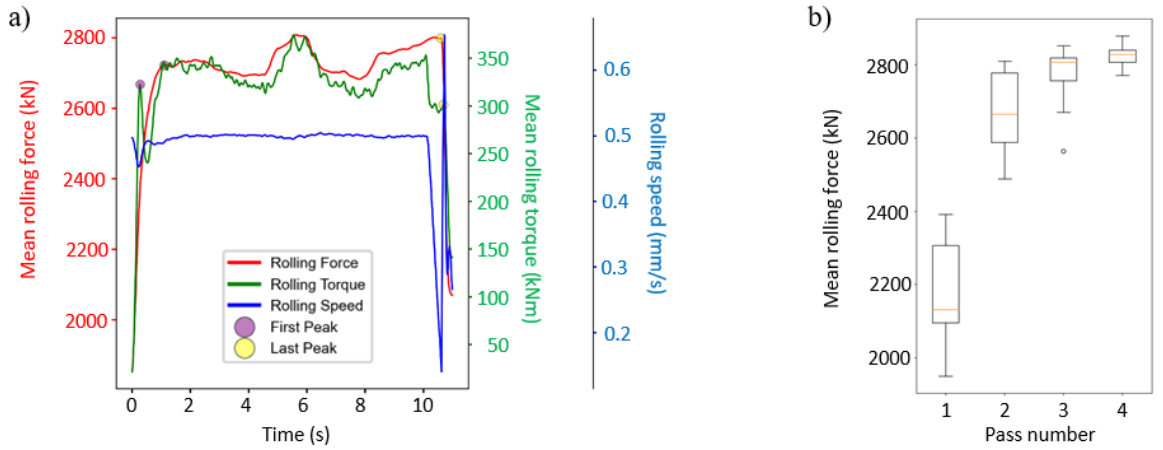


Figure 5. Example of automatically generated images for cold rolling. a): Process data of a pass. b): Aggregation of the mean rolling forces over the 4 cold rolling passes.

To get a better understanding of technical implementation of the data pipeline, the following section provides a detailed explanation of the data pipeline process, exemplified by the process of press hardening. The process data for press hardening is measured by two separate systems. The pressing force and the displacement are stored internally by the control unit of the deep drawing press as a time-series csv-file. The tool temperature measurements by the integrated thermocouples is saved on a thermal measurement system as a time series csv-file. Metadata is logged manually in a xlsx-file on a cloud-based storage system, in which the press data and temperature data files are uploaded. Using a Python script and well-establish libraries like Numpy and Pandas, the data is automatically synchronized by determining the start of the press stroke. After general cleaning and reduction of the data to the relevant time window, the actual holding time during quenching as well as the initial tool temperature is calculated and displayed together with the calculated forming force, displacement, and tool temperature change during and after the hot stamping, as seen in Figure 6.

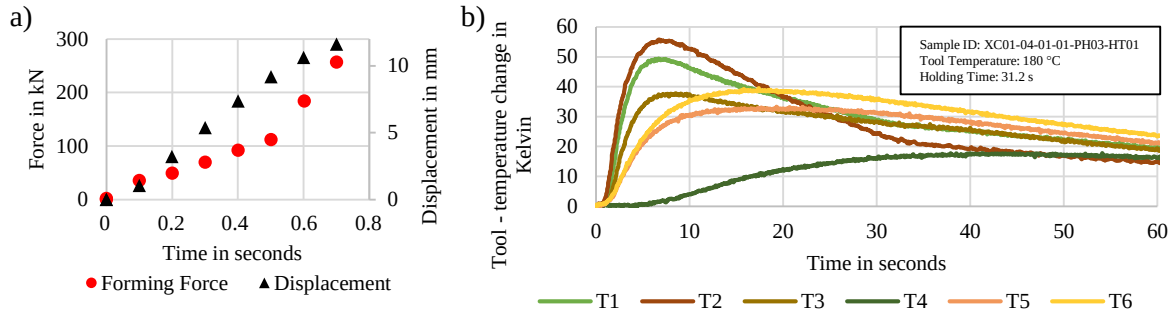


Figure 6. Example of automatically generated data for press hardening; a) forming force and displacement over process time b) temperature change of die for the first minute after start of the stroke.

Additionally, all features shown in Table 2 are automatically extracted within seconds, linked with the corresponding ID and saved for all parts in one xlsx-file. Typical and often used relationships, e.g. distribution of mean rolling force by pass number are directly visualized. Furthermore, the data can be used as a basis for customizing a DMS in order to solve specific issues. Two possible applications of these extracted features are shown in the following chapter.

Table 2. Overview of automatically extracted features.

Cold Rolling	Rolling Force, avg. Rolling Force, max. Rolling Force	Rolling Torque, avg. Rolling Torque, max. Rolling Torque	Thickness reduction, Hardness
Press Hardening	Displacement, Force, max. Forming Force, Holding time	Tool Temperature, max. cum. Temperature increase, avg. cum. Temperature increase, Rate of cum. Temperature increase	Cracks, Hardness

4.3. Exemplary demonstration of the results of the implemented data pipeline

Alongside the previously mentioned processing, aggregation and visualisation of process data, both regression and classification algorithms were utilised to showcase the capabilities of the developed data pipeline. The classification as well as the regression were carried out with algorithms provided by MathWorks Matlab Toolbox Classification Learner and Regression Learner. The aggregated process data from which both algorithms were trained, was taken from the process chain of press-hardened parts presented in chapter 3. In addition, the hardness measurements were used, too.

To illustrate the classification, an algorithm was used to detect the presence of cracks in the press-hardened part using process data. For the training, the press-hardened parts were categorised manually into the "No Cracks" or "Cracks" class (observed cracks) and that information was forwarded to the algorithms. After training, a fine tree algorithm was able to correctly classify (predicted cracks) almost 86% of the parts based on the tool temperature, the maximum force, and three features of the temperature measurement. The result is shown in Figure 7 a, all parts with “No Cracks” were correctly assigned (100%). However, 28.6 % of the parts with “Cracks” were incorrectly assigned. The initial findings are satisfactory, indicating chance for further improvement with additional (simulation) data.

Beside the classification example, regression algorithms were trained to predict the hardness (HV1) of the press-hardened parts. To train the algorithms only the hardness measurements from press-hardened parts without cracks were used in order to use consistent data. The hardness after the press hardening was predicted using the tool temperature, the cold-rolled sheet hardness, the maximal measured force and exactly like in the crack classification example three temperature features. The best result is shown in Figure 7 b. A clear trend can be recognised, although the predictions still deviate from the measured values. Similar to the classification example, it is also clear here that there is potential for further improvements. Presently, there are some manual elements that undermine the precision of data-driven approaches, such as the manual loading and unloading of the component into and out of the press and the manual measurement of hardness. Considering these factors, both outcomes seem optimistic because it becomes clear that correlations can be recognised despite manual influences and a manageable amount of data, thus showing potential for deeper understanding of material behaviour in combination with numerical simulations.

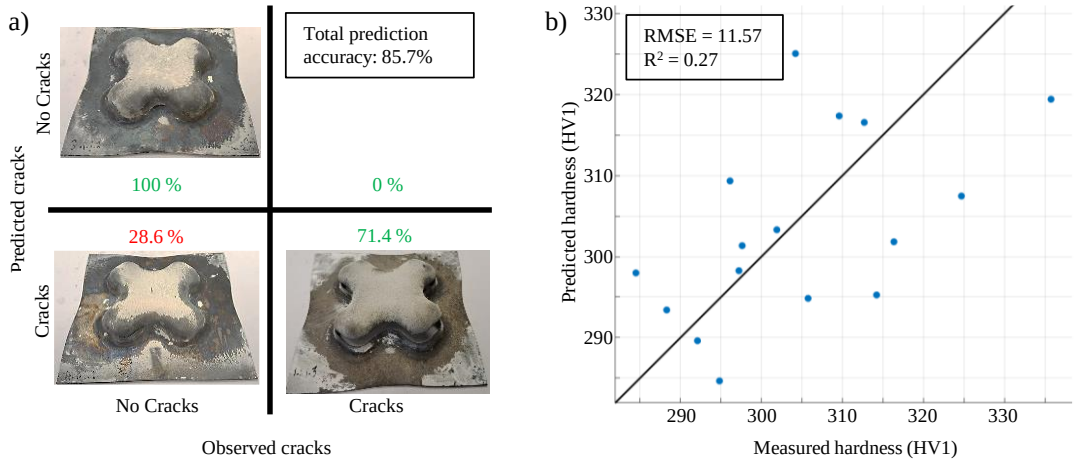


Figure 7. Results of parameter correlation and prediction on a) crack probability and b) hardness.

5. Summary and outlook

This paper presents a data processing framework for press hardening of MMnS, encompassing cold-rolling and hot-stamping with an integrated identification system, linking data across processes and sensor systems. The developed framework enables the usage of DMS for deeper understanding and discovering of complex relationships between process parameters and material properties of the final part. The framework enhances understanding of complex process-material relationships and is exemplified by statistically correlating crack probability and hardness with process data.

In future research, the data processed can be utilised to conduct numerical simulations which yield valuable information that may be otherwise impossible to measure, e.g. cooling rate during press hardening. This data and information can be used to produce a digital twin, accurately detailing each element and allowing for thorough analysis. Combining this principle with fast material models could enable new possibilities of process monitoring by online calculation of material properties based on real-time process data.

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