Implementing new Approaches of Digitization in Conventional Metal Forming Processes: A German perspective

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Abstract. The Institute for Metal Forming Technology (IFU) at the University of Stuttgart / Germany since more than six years strongly strives to future oriented research work focusing on far-reaching concepts for digitization of metal forming processes. Main activities of engaged research groups are integrating sensors and actuators into metal forming machines or dies to analyse process data gained that way. Also, development of advanced methods for production data mining are related to those fields of activities. The paper therefore highlights strategies and practical applications of such digitization concepts. Also, important issues in terms of metal forming production processes will be addressed such as avoidance of scrap during ramp up phases and batch processing. Finally, the practical use of machine learning algorithms will be demonstrated in real trimming and metal forming processes.

1 Introduction and State of the Art

Digitalization in metal forming and punching technologies aims to improve the effectiveness and efficiency of batch processes. One of the main objectives is to support companies in their strategic strive for economic and ecological benefits. Inspired by the cooperation with several industrial project partners, recent research at the Institute for Metal Forming Technology at the University of Stuttgart (Germany) focusses on the following topics:

- Development of a new data-driven approach to improve part quality in bulk metal forming processes [1]
- Development of inline material testing methods for punching processes [2]
- Evaluation of feature engineering methods in order to improve the predictive capabilities of Machine Learning models in the context of punching technologies [3]
- Image based quality monitoring of deep drawn sheet metal parts [4]
- Data-driven design of novel shear cutting processes [5]
- Prediction of cutting surface parameters in punching processes [6]
- Data-driven methods for tool wear detection in shearing and punching processes [7]

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The investigation of the above-mentioned research areas was based on numerical simulation results and experimentally gathered process data. In recent years, machine learning methods such as decision trees, support vector machines and artificial neural networks have gained in importance due to their role in data analysis and processing in these areas. Nevertheless, the use of machine learning algorithms is still an inexperienced domain for many manufacturing companies in metal forming industries. In this keynote paper, we therefore want to highlight two use cases for digitalization in cold forging and sheet metal processing.

2 A new approach to improve part quality in bulk metal forming

This section highlights the use of sensor technology for data acquisition and how these methods advance the digitization of bulk metal forming. Digitization of conventional cold forging processes can lead to increased efficiency, automation, and eco-friendliness with simultaneous reduction in scrap production. Furthermore, sensor data support the analysis of long-term production trends, essential for addressing product recalls. The connection between production data and the final product, including innovative, mark-free identification and measurement techniques for cold-forged parts is investigated. This novel approach contains the use of innovative inspection sphere by Fraunhofer Institute for Physical Measurement Techniques (IPMinspection). Using this sphere, a unique "part fingerprint" resulting from the metallic surface structure can be detected for both long-term trend analyses and immediate process adjustments). By assigning process data to the respective fingerprint, it is possible to perform long-term trend analysis and immediate process adjustments. Emphasizing the ramp-up phase, we aim to minimize scrap via AI-controlled adjustments of the punch position, utilizing real-time sensor data for precise process management and scrap tracking.

2.1 Experimental setup

The experimental setup at IFU Stuttgart utilizes a Schuler MSL 1-500-0,85-500 servo-mechanical press with a 5,000 kN force capacity for cold forging, utilizing a tool for three-stage synchronous forging and ejection as shown in Fig. 1a [1]. The automated experimental tool shown in Fig. 1a was developed for synchronous cold forging and subsequent ejection for three forming operations. The tool frame has four column guides and three dies with an outer diameter of Ø160 mm can be mounted in the lower part of the frame. Measurement tools such as force rings, load cells for punch force, and thermocouples for temperature monitoring are integral parts of the system. Capable of operating at up to 25 strokes/min, the setup is automated with control panels, conveyors, separators, and a gripper transfer system. Following the forging process, parts are directed to an inspection sphere developed by the Fraunhofer IPM [8][9].

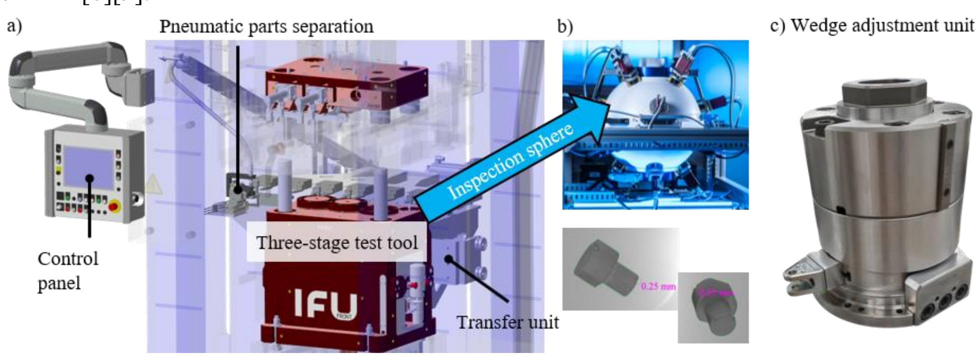

Fig. 1: a) Three-stage test tool. **b)** Inspection sphere [9][10] **c)** Wedge adjustment unit

This innovative inspection sphere, designed for real-time geometric data and part tracking, comprises two hollow hemispheres equipped with 16 high-resolution cameras and light barriers that activate the cameras upon part entry. Shadow-free, diffuse illumination by two LED rings at the sphere's openings facilitates motion blur-free imaging during the part's free fall - a crucial feature for capturing clear images in limited observation time. A pneumatic separator positioned below the sphere is tasked with sorting defective parts. The camera setup and calibration have been meticulously optimized, employing a Charuco-patterned calibration body for precise camera calibration and part orientation detection relative to a global coordinate system. In collaboration with Visometry GmbH, Fraunhofer IPM is advancing software for efficient data processing from the sphere, with initial tests showing the capability to identify component fingerprints in under 0.1 seconds and compress them to less than 10 kB. The sphere is able to detect objects ranging from minimal dimensions of 5 x 5 x 5 mm up to a maximum of 60 x 60 x 60 mm within 0.2 seconds and identifying surface defects as small as 30 µm [9].

Additionally, the shown setup incorporates a motor-driven wedge adjustment system for precise punch positioning (see Fig. 1 c), allowing for adjustments within sub-micrometer accuracy. This self-locking system, innovated by IFU, comprises stacked wedges for fine adjustment, operating in a closed-loop system for unmatched precision under load. A machine learning model, trained with both numerical and experimental data, oversees punch positioning, with adjustments finely limited to 0.5 mm, ensuring high accuracy and efficiency in the forging process.

2.2 Preliminary investigations on ramp-up phases in cold forging

The ramp-up phase of the process described here was analyzed through numerical and experimental methods to understand the correlation between process parameters and part dimensions. An automated single-stage cold forging process, specifically backward cup extrusion using C15 steel at 9 strokes/min, was investigated to gather initial data. This process was chosen due to its significant tribological and forming loads, which quickly increase the punch temperature, affecting its length and the dimensions of the formed part, measurable through the base thickness of the extruded cup.

In the experiments the punch force as well as the stroke were measured. Also, the die temperature was measured using a type K thermocouple placed 2 mm below the active die surface. Results showed a "saw tooth shaped" profile of punch force and tool temperature, indicating maximum loads per stroke (see Fig. 2). While punch force remained constant, tool temperature rapidly increased within the first 50 strokes to a saturation temperature of around 65 °C, indicating a steady state. This temperature increase led to a 1.5 % reduction in cup base thickness due to thermal elongation of the punch, suggesting the end of the ramp-up phase after extruding approximately 250 components. This information served to estimate the wedge adjustment range, the die temperature saturation during cold extrusion, and changes in part geometry during the ramp-up phase.

Additionally, a demonstrator multi-stage cold forging process was modeled using Deform2D™ software. A test bench geometry featuring a flat surface for Fingerprint ID detection and a non-rotationally symmetrical shape for orientation determination within the inspection sphere was established. The workpiece, designed with dimensions Ø23 mm x 30 mm and flattened sides on the screw head for improved pose estimation, was simplified in the simulation for efficiency, minimizing calculation time without significantly affecting results.

The simulation involved modeling the cold forging sequence with the workpiece made of C15 steel undergoing sequential forming operations. Heat transfer processes were simulated to account for heat loss from the workpiece to its environment, mimicking the real press's

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ram movement at 25 strokes/min. Due to computational constraints, the die temperature for multi-stage forging was analyzed by sequentially processing single workpieces, with thermal processes for inactive tools paused and their temperatures applied to subsequent parts. Initially focusing on the setting stage, the process then looped through the next stages for a total of 1.000 cycles.

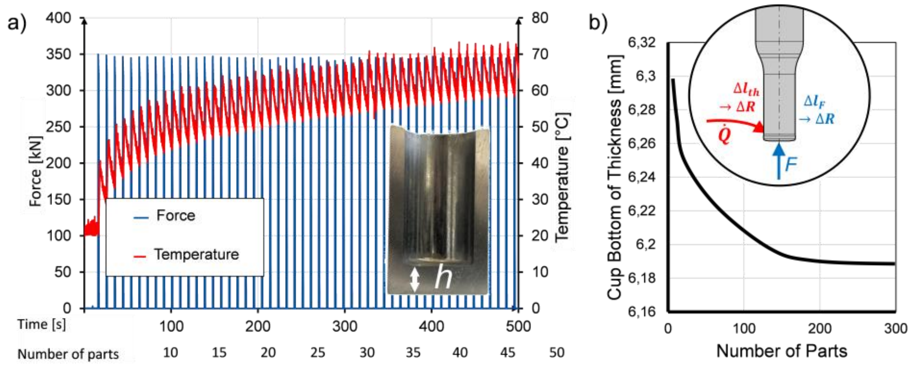
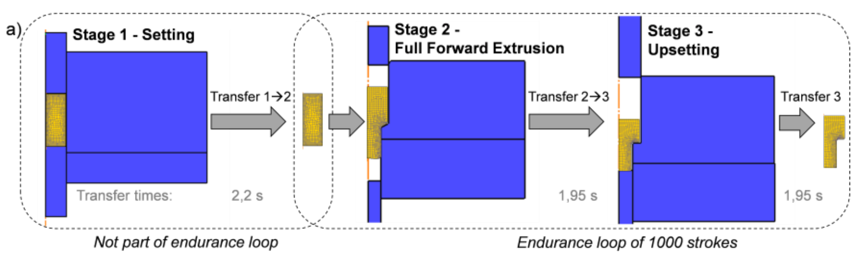
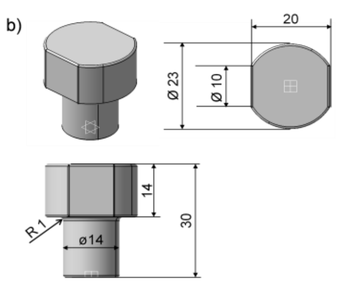


Fig. 2: Measurement results of the endurance test with backward cup extrusion with material C15, a) punch force and die temperature, b) cup base thickness.

Numerical results show tool temperature profiles reaching saturation after certain numbers of strokes: 57 °C after about 450 strokes for full forward extrusion and 59 °C after around 650 strokes for the head upsetting stage. Additionally, the impact of tool temperatures on elastic behavior was assessed, revealing increased radial die widening by 1.9 µm in full forward extrusion and 3.5 µm in head upsetting compared to the baseline temperature of 20 °C.





c)

Simulation parameters	
Software	DEFORM 2D
Mesh workpiece	900 Elements
Minimum mesh element size	0.25 mm
Workpiece material	C15, plastic
Tools	rigid
Initial process temperatur	20 °C
Friction	shear, 0,12
Stroke rate	25 strokes/min
Simulation type	Lagrangian incremental
Solver	SPOOLES

Fig. 3: Numerical investigations on multi-stage cold extrusion process, a) Simulation setup, b) final workpiece, c) simulation parameters.

2.3 Approach for combined use of inspection sphere and the wedge adjustment control

To enhance cold forging processes, two main strategies exist: quick process stabilization and continuous adjustment of conditions [1]. The former aims to eliminate ramp-up phase transients through methods like pre-heating tools/blanks or using specific tool materials to limit thermal expansion. The latter strategy adapts to changes affecting quality, utilizing mechanical/electrical actuators and intelligent data processing to shorten ramp-up phases and stabilize processes. Actuators may involve elastomer inlays, hydraulic pressure, shape memory alloys, or dies with active thermal management to modulate process conditions.

Continuous adjustment, leveraging real-time data analysis from tools like the novel inspection sphere by Fraunhofer IPM, offers a promising potential for process improvement. This way, via the inspection sphere with thermal punch elongation control, using a new wedge adjustment unit, a 100% component monitoring is possible. This integration enables data-driven punch position adjustments ($\Delta z1$ and $\Delta z2$, illustrated in Fig. 4), informed by trends and correlations between process data and part dimensions, aiding machine operators with clear insights. Both conventional and AI-based controls can output adjustment settings, enhancing process efficiency and material utilization.

This innovative approach supports digitization in cold forging, potentially reducing CO_2-emissions and scrap production, thus increasing economic efficiency. The wedge adjustment unit's compact size allows for broad press integration, and the inspection sphere's flexibility accommodates various workpiece types. Implementing this system could enable near-zero scrap production and retrospective workpiece failure analysis, enhancing material use and potentially replacing some machining processes.

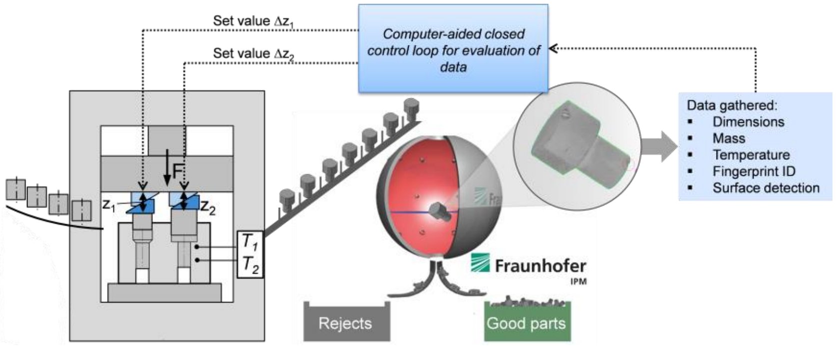


Fig. 4: Principle concept for the combined use of inspection sphere observation of workpieces and wedge adjustment control [10]

3 New Approach to determine sheet metal properties from punching force curves

The increasing digitalization of production processes is opening up new possibilities and potential for monitoring forming and stamping processes. The quality of the components produced by these processes is highly dependent on the properties of the sheet metal material. Therefore, maintaining a continuous digital record of material data offers significant potential for monitoring the quality of each component throughout production. Since almost every sheet metal component is trimmed or punched during the manufacturing process, our proposed approach is to utilize existing hardware in forming and cutting tools for inline material evaluation. A newly developed and previously published [2] materials testing method exploits analogies between cutting force curves recorded during the manufacturing process and stress-strain curves obtained by conventional testing methods for material characterization. This new method is presented in Fig 5. The method exploits the consistent identification of three characteristic areas in both sets of curves (elastic & plastic deformation and fracture). Analytical correlations exist for the maxima of the two measured curves. However, analogous analytical relationships (white models) for the inverse calculation of additional mechanical material properties need to be established.

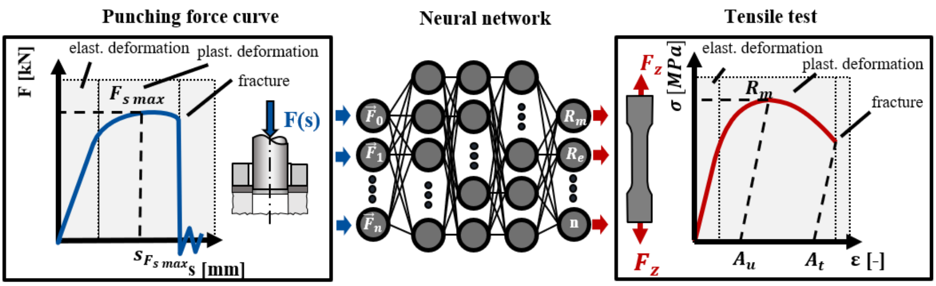


Fig. 5: Analogies between cutting force curves **(left side)** and stress-strain diagrams **(right side)** and neural network-based approach to predict mechanical sheet metal parameters from experimentally measured punching force curves **(middle)** [2]

The approach of our newly developed material testing method is to use measured cutting force curves as input vectors for a neural network. The neural network is then trained on output variables obtained from the uniaxial tensile test. The following sections will show that this deep learning approach provides a promising new method for inline evaluation of mechanical sheet metal parameters.

3.1 Experimental Setup

In order to train an artificial neural network (ANN), the cutting force curves and mechanical properties of various sheet metal materials, including DC03, DP600, DP800, DP1000, DP1200, HX380 and DX54, were determined experimentally. The experiments were carried out using a modular test tool equipped with a load cell (Kistler 9104A) designed for direct force measurement during punching. A sectional view of the tool is presented in Fig. 6. Table 1 states the punching parameters used.

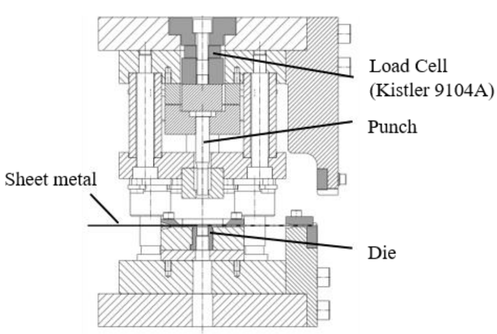


Table 1: Punching parameters

Parameter	Value
Length of punch	80 mm
Cutting clearance	15 %
Punch diameter	10 mm
Sheet Thickness	1 mm
Stroke	100 1/min

Fig. 6: Schematic sectional view through the test tool

The experimental investigations to determine the tensile properties of the different sheet metal materials were carried out on a Roell + Korthaus RKM 100 Material Testing Machine according to DIN EN ISO 6892-1. The determined stress-strain curves as well the measured punching force curves are depicted in Fig. 7.

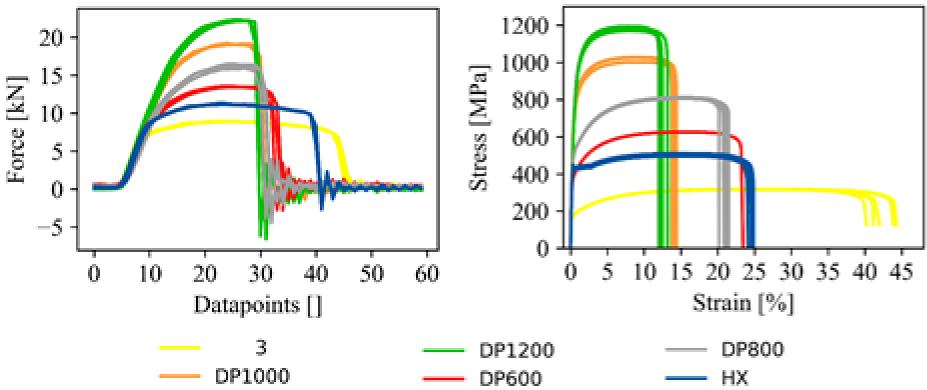


Fig. 7: Experimentally determined punching force curves (left side) and stress-strain curves (right side) [2]

3.2 Data Preparation, Model Training and Results

The process of training a neural network involves several steps: Data acquisition, pre-processing, model building and training. In this study, the data preparation phase focused on filtering the punching force curves to remove oscillations caused by the machine structure and tooling, particularly during workpiece separation at the end of punching (see Figure 3, left). The force values below 4 kN were set to zero. In addition, data augmentation, a widely used technique for generating diverse data sets, was used. Each measured force curve was multiplied by 20 NumPy random arrays with a standard deviation of 0.5%, simulating the dynamic noise found in stamping processes. This expanded data set, provided diverse data for model training. In total, 480 artificially vibration-superimposed cutting force curves were used for model training after this augmentation process.

A fully connected feed-forward neural network (FFNN) with four hidden layers was used to build the model. The architecture included 64 neurons for the first hidden layer and 32 neurons for each subsequent layer. Sigmoid activation was applied to the first, second and fourth hidden layers, with ReLU used for the second layer. The input consisted of 60 data points from each force curve, while the output vector included the material parameters Rm, R_e/R_{p02}, A_g, A_t and the strain hardening exponent n. To avoid overfitting, an 85%-15% test-train split of the extended dataset was implemented. This ensured effective training on the training set while allowing generalization to unseen data (e.g. sheet metal material DX54). Model training converged after 200 epochs without overfitting. In Figure 8 (left), the plots compare the neural network output with tensile test values for different sheet materials. The coefficient of determination was calculated for each predicted material parameter to assess the prediction accuracies. A coefficient of determination of 0.97 was achieved for the hardening exponent, while coefficients of determination greater than 0.99 were achieved for the predicted tensile strengths, yield strengths, fracture strains and uniform strains. Given the strong agreement between the model output and the target values, it can be concluded that a trained neural network can accurately predict sheet metal properties from experimentally measured cutting force curves. Furthermore, as shown in Figure 8 (right), the trained neural network showed accurate predictions for tensile strength, yield strength, fracture strain, uniform strain and hardening coefficient for the "unseen" sheet material DX54.

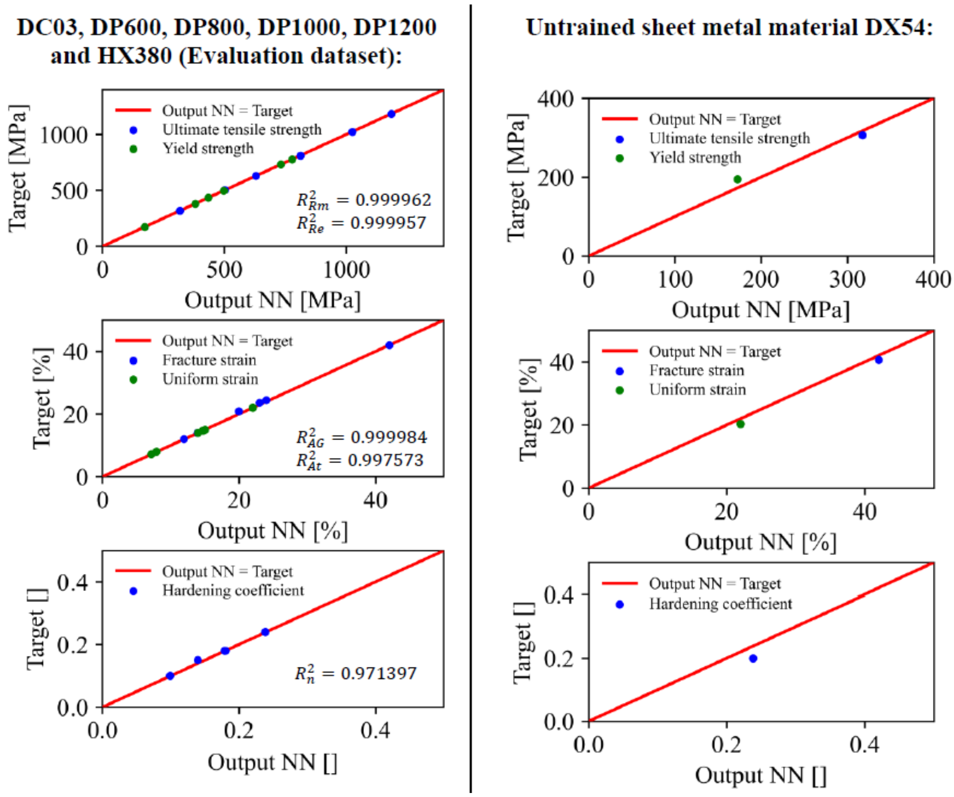


Fig 8: Comparison between the predicted sheet metal parameters (Output) and the values from tensile tests for the validation dataset (left side) and for the untrained sheet metal DX54 (right side).

4 Summary and Conclusions

This paper presents new approaches to digitization in bulk metal forming and in punching technologies, emphasizing the strategic advantages of data-driven methodologies. These approaches, developed at the Institute for Metal Forming Technology (University of Stuttgart), lead to significant enhancement of effectiveness and efficiency of batch processes. The hereby presented approach in the field of bulk metal forming elucidates the integration of advanced technologies such as an innovative inspection sphere and a wedge adjustment unit, facilitating 100 % component monitoring and precision in thermal punch elongation control. This way not only the quality of parts produced can be enhanced but also scrap and CO_2 emissions can be reduced significantly.

The method presented for digitizing stamping processes provides the possibility of determining material parameters from stamping force curves. This dramatically expands the possibilities for inline material evaluation and offers a variety of new possibilities for process monitoring and control in current manufacturing processes.

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