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TOOLING SYSTEMS WITH INTEGRATED SENSORS ENABLING DATA BASED PROCESS OPTIMIZATION

Sensor integration into machining equipment has become an important factor for gaining deep process insights mainly driven by increasingly smaller and cheaper sensors and transmitters. Due to advances in microelectronics and communication technology, a broader field of applications in production processes and machine tools can be addressed using sensing devices and their implementation potentials. Ensuring a sensitive but robust data stream from close to the actual process allows not only reliable monitoring but also process and quality control based on sensor information. This paper provides an overview of the utilization of sensor data for the purpose of condition monitoring, model fitting and real-time control coping with stochastic effects. Examples of sensor integration in fields of injection molding, roll forming and heavy-duty milling comprise the state of the art of sensor implementation, data evaluation and possible feedback loops in the respective application scenarios.

1. INTRODUCTION

Motivated by the aim of achieving high quality in processes and parts, reduction of setup time and process understanding, sensor integration is becoming increasingly important (see [1]). This paper shows sophisticated possibilities for sensor-equipped processes and summarizes the state of the art of process monitoring and control briefly.

Sensors on semiconductor basis, piezo-resistive strain gauges and piezoelectric sensors were developed with the spread of the silicon technology in the 1970s. Since then, innovations like “system on chip” (SoC) and integrated MEMS (Micro Electro Mechanical Systems) together with further miniaturization, increasing intelligence and decreasing prices of such components led to today’s sensor technology [2]. The application areas for tool system integrated sensors are subject to competing requirements for time response or location of sensors. The used sensors are usually selected with respect to their sensitivity, reliability, costs and the measured parameters that are fundamental to the process being observed. As

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modern manufacturing processes become more and more complex, the benefits of enhanced sensor-use increased. Tooling applications including sensor systems which are inexpensive, robust for the use in the processing environment and easy to use are required. In addition, there must be an overriding advantage for the user that is in proportion to the costs incurred by the additional sensors. Jemielniak states in [3] that also user friendliness and reliability are required for industrially applicable systems.



Fig. 1. Overcoming limits of conventional processes

Leading towards improvements in process efficiency and quality, as well as providing enhanced applicability requires overcoming existing limits of conventional processes, as summarized in Fig 1. In particular, stochastic phenomena such as geometry and shape deviations of raw parts due to preliminary processes like casting, forming or even 3D-printing together with changing material properties of raw material batches take significant influence in industrial process application. In conventional processes, these aspects often cause a conservative setting of process parameters and thus reduce the economic efficiency. A reasonable approach to meet modern requirements in manufacturing processes and to handle stochastically occurring events is the integration of sensors for monitoring and control purposes [3, 4]. However, this allows measurement and direct optimization of the conventional production process, monitoring, adaptive process control and fitting of model parameters for the setup and validation from simulations e.g. digital twins and CPPS (Cyber Physical Production Systems) [5, 6].

One common feature of all of the following sensor integration scenarios is the location of the sensor in the nearest part of the process being not a consumable or the product itself. The long lifespan of a cavity mold, a roll forming stand and a tool holder allows an important decrease of costs of sensitization.

Ensuring part quality in highly repetitive processes, like injection molding, is enabled by detecting temperature and pressure [7] as well as heat flux [8] in the cavities. Furthermore, this data can be used to enable feature learning in the course of data-based process monitoring [9]. In [10], Monostori states another possibility for modeling and monitoring of manufacturing processes, which can be realized by combining sensor integration with artificial neural networks techniques.

Gaining deep insight about complex forming processes via sensor integration is highlighted by roll forming, where a different approach arises. An increased repeatability, a reduction of setup time and constant process parameters can be achieved by sensor integration into multi-step forming processes like roll forming. Like in many other application scenarios, contact normal forces in the individual forming steps [11] and the drive torques applied by the drive of such plants [12] are monitored. The manufactured product is mainly controlled by scanning the generated geometry [13]. The acquired measurement data can in turn be used to deepen the understanding of the entire roll forming process [14] and to derive optimizations concerning the tool geometry [15]. By correctly interpreting this data, adjustments of the roll forming line can be made to ensure the desired high-quality output of the product. Furthermore, there are current studies dealing with set up times [16] and the validation of simulation models of the process [17, 18].

Process control based on sensor integration in machining processes finally shows the potential of all three aspects of Fig 1. For instance, sensor integration in positions like in the work piece or e.g. in milling tools [19] lead to a new sensor for each produced part or substituted tool. Thus, the measurement of vibrations [20, 21] and accelerations [22] for the detection of unfavorable machining- or process conditions, tool wear or even a crash become possible. Another advantage of sensor integration into tools can be found in a rather direct transmission behavior with little influence of other machine parts in the vicinity of the process compared to other methods like monitoring the motor current or the acoustic emission characteristics of the process [23, 24]. At locations rather remote to the actual process, thermally induced changes in machine behavior [25], mechanical coupling and external disturbances easily play a major role when process conditions are measured.

The extensive use of sensor information enables significant perspectives in the development of computer science, information and communication technologies in manufacturing systems. Monostori in [26] states, that collaborating computational entities which are in intensive connection with the production systems represent CPPS. The system structure of tools with integrated sensors for data acquisition close to the process provides information preferably in real-time and uses data-accessing and data-processing services available on both, internal information platforms or e.g. via web by the use of cloud systems. Four strategies (not exclusive) can be envisioned for the use of this information:

- process near data acquisition, which will be used for process optimization,
- establishing a knowledge base by capturing and monitoring of the empirical process effects for subsequent optimization or new process design,
- direct measurements from tool integrated sensors for feedback to controllers enabling process adaption by heuristic or physic-based rules,
- information feedback and validation of process models, that allow the performance to be predicted.

For further elaboration, a comprehensive overview of sensor technologies, of signal processing and decision-making strategies is given by Teti et al in [27]. Overall serial production like injection molding, complex multistage processes like roll forming and batch-size-1 processes with large impact of stochastic effects, sensor integration has a large potential enabling data-based process optimization.

2. UTILIZING SENSOR DATA

Referring to the above mentioned four aspects of sensor information utilization, one option is the use of gained data from different sources for monitoring the condition of the process, the tool and the work piece. Due to these efforts, it is possible to achieve an increase in interesting aspects for quality control, predictive maintenance and cost reduction.

Firstly, sensing the process' condition can lead to real time evaluated process monitoring, causing alerts or drawing graphs in the near surroundings of the machine tool user like in Fig. 2A. Besides sensor information for tool condition monitoring like in [1] or additionally in [3, 4, 28], data of the NC can be used as additional information for anomaly detection [29]. These kinds of evaluation are often based on key figures and fixed rule engines to provide a real-time statement for online and inline analyses. Data visualization can be provided by monitors and cellphone apps as well [30].

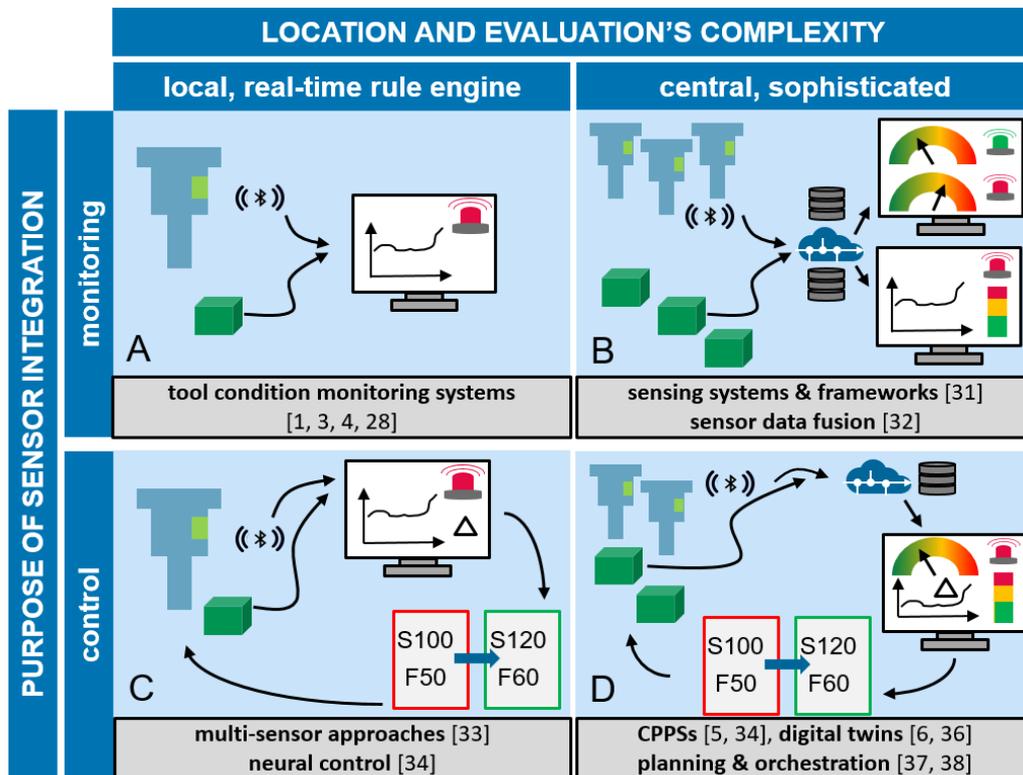


Fig. 2. Overview of benefits by sensor integration

Secondly, sensor data can be pushed up in a higher level of hierarchy to support a holistic surveillance of several sources within one or several machine tools at a production site. Like in Fig. 2B, data can be accumulated via networks or cloud services [32, 33]. Merging different sensors' signals and correlating signal characteristics to tool wear and work piece quality can be used for training algorithms, as shown by Möhring in [39]. With high computational power for teaching and training, artificial intelligence and machine learning

can be addressed [40]. Thus, simple rule engines for time-sensitive systems (Fig. 2A & C) can be developed and adjusted out of simulations or models of high complexity. Moreover, cost benefits can be achieved by in-process monitoring with real-time capabilities of signal processing and a feedback loop enabling a reduction of scrap parts by direct interaction and parameter adaptation.

Similar to these levels of monitoring strategies, process control via feedback loops can be accomplished. A rather simple rule engine, for instance running on an industrial PC [41], and local countermeasures are needed for a real-time process control, like in Fig. 2C. Once again, various data sources connected via networks and databases can be utilized for a sophisticated evaluation to adjust process parameters (Fig. 2D). In this context, aspects of data storage, administration and information strategies require interdisciplinary cooperation with fields of computer science. In this regard, the European initiative of GAIA-X sets a new framework and standards. Rather long-term feedback loops can be set up, also involving production planning and CAM (computer aided manufacturing). Nevertheless, in terms of digital twins, complex sensor integrated feedback loops are getting faster and suitable for on-line measurement [42] and aiming for real-time adaptation [43].

3. USE-CASE INJECTION MOLDING

Injection molding is an important process for mass production of plastic parts with high demands on their quality, especially dimensional accuracy and surface, as well as complex geometries. A sensor-equipped tool provides methods for process monitoring to detect insufficient quality of produced parts like surface defects. To achieve high process stability consistently, the cycles of the injection molding process have to be as identical as possible. An adequate setup of the machine and process parameters can be derived via identification from process monitoring [44, 45].

In recent years, various approaches have been presented and introduced to monitor process parameters of injection molding in real-time and furthermore to reduce common quality defects such as warpage or shrinkage [46–49]. Many sensor-supported monitoring systems for measuring pressure and temperature are used for process monitoring of injection molding in order to obtain an insight into the injection molding process [50, 51]. Furthermore, there is a lot of potential for developing a control system as injection molding machines are able to learn the operations supported by machine learning and big data [52, 53].

3.1. SENSOR INTEGRATION IN MOLDS

Cavity pressure measurement provides precise information about the injection process and is a widely acknowledged basis [54, 55, 56] for process monitoring, controlling and indicating errors of injection molding processes. As shown in a previous study dealing with the development of smart monitoring [57], cavity pressure sensors and temperature sensors are used to derive the optimal process window to reduce the number of scrap parts.

A combined pressure and temperature sensor for mold and polymer, e.g. a triple-combined FOS-sensor of FOS-Messtechnik GmbH, suits well for the simultaneous measurement of cavity pressure and melting temperature, which subsequently can be used for calculating process-specific rheological properties [58]. The identification of correlation between process parameters of injection molding and final part quality, classified on visual inspection of the specimens and their weight, is shown in [59]. Another study in [60] identified common process parameters such as cavity pressure and switching point to holding pressure, which are then used to forecast unplanned machine downtime. Further research in [61] shows that varying process parameter settings, like switching point, can be reflected in cavity pressure profiles. The following example focuses on the measurement of cavity pressure and the switching point between injection and holding pressure, which is visible in the pressure curve.

3.2. EXPERIMENTAL SETUP FOR MONITORING CAVITY PRESSURE

The data used in this setup was acquired from a triple-combined FOS-sensor, type MTPS 408-IR-BTS-XSR, installed in the mold cavity of an “Engel ES600/100 HLSEL” injection molding machine with an EC100/CC100 control unit. The configuration of the used sensor and the structure of cavity are illustrated in Fig. 3. The focused part is an ISO 20753 multipurpose test specimen type A1 [62] and the used material is Novodur HH-112 Acrylonitrile Butadiene Styrene (ABS). The experiments depict differences in pressure and part quality between three different settings of pressure properties. The switching point defines where low pressure, used for filling the mold, turns to high pressure for finalizing the molded part.

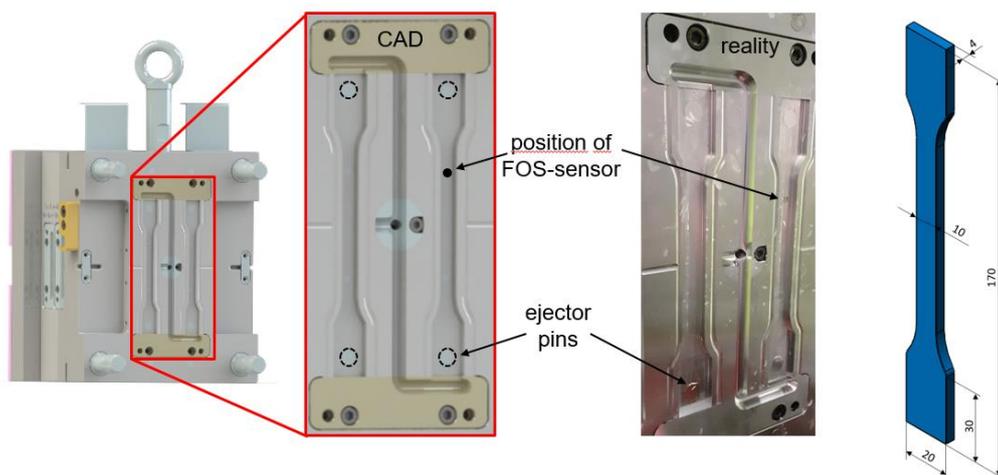


Fig. 3. CAD model, real mold with embedded sensors and CAD model of test specimen

Each single switching point setting was used to produce 5 individual parts, leading to a total of 15 parts and the corresponding sensor data. While all three settings show similar tensile strength, the varying quality features for classifying differences are the mass of the

produced test specimen and the degree of filling the edges of the cavity. Fig. 4 shows the experimental results for cavity pressure regarding different switching points.

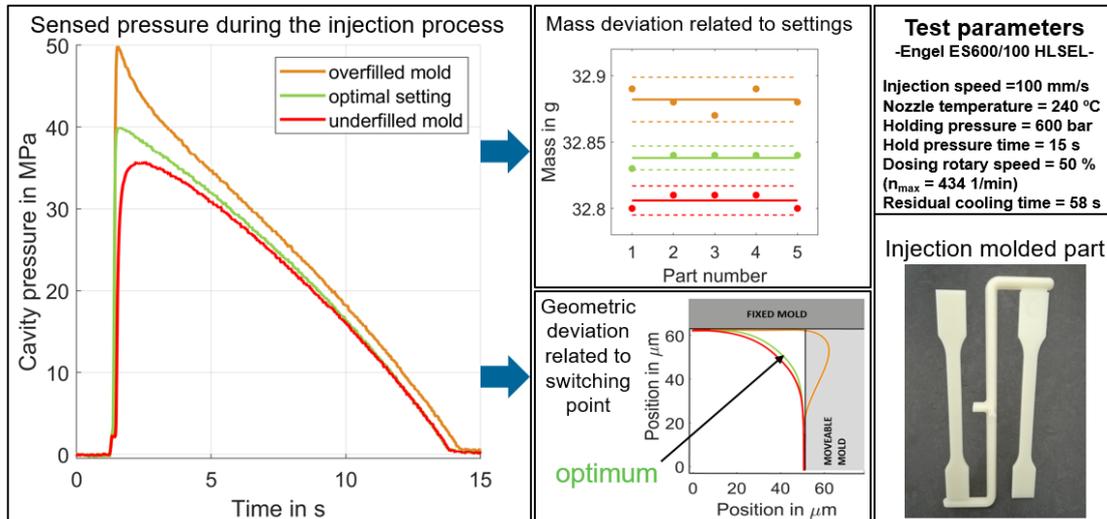


Fig. 4. Pressure during the injection molding process and resulting deviation of mass related to switching point for the given test parameters

By comparing the patterns of the cavity pressure, it becomes evident, that each switching point results in a different pressure profile. The red cavity pressure profile in Fig. 4 (left) shows an injection pressure that is insufficient to compress the melted polymer and fill the provided cavity, resulting in a short shot, sink mark and warpage. In addition, the edges are not filled sharply. As depicted by the orange curve in Fig 4, the pressure can also indicate overfilling of the cavity, leading to higher mass of the work pieces. An adequately set switching point leads to the aspired pressure, so that the melted polymer accomplishes a complete filling of the cavity without overfilling, but also generates sufficient compression of the melted polymer in the cavity. The characteristic cavity pressure profile of a properly adapted switching point illustrates the green line in Fig. 4 (left). Process monitoring and the potential of combined autonomous process controlling are important aspects to keep the quality of the produced parts constant and to avoid severe damage to the mold. Forecasting, stabilizing and assuring quality in mass production processes provide economic advantages based on sensor integration.

4. USE-CASE ROLL FORMING

The second example of sensor integration in tooling systems is a forming process. In many metal forming processes, intelligent tools with integrated sensors are used to monitor and control the process. Yang [63] gives an overview of smart metal forming by using die-embedded sensors. Kim [64] used bolt type piezo-sensors to measure the load on the die, Hagino [65] used ultrasonic sensors to measure contact states between the work pieces and

the die. Yang [66] further used acoustic emission sensors for the detection of friction sources. In the following, the faced problems and chances through sensor integration in forming processes are discussed on the chosen example of roll forming. This process is a continuous, incremental forming process where a sheet of metal is formed through pairs of contoured rolls, which are aligned on shafts. The outer contour of these tools defines the shape of the produced profile. Up to 60 of these pairs of forming rolls are used to form the desired profile on a conventional roll forming line. Additionally, processes like welding, punching etc. allow to form very complex profile geometries used in a broad field of applications like building, agriculture, furniture etc. Roll forming is a process suitable for large quantities due to high production speeds. Therefore, these application scenarios provide great potential to overcome limits of non-sensorized settings.

One of the challenges of the roll forming process compared to others are the high changeover times of roll forming lines for new work piece geometries and even for follow-up productions. As the market demands higher flexibility and therefore smaller batch sizes, high number of changeover events and the resulting time efforts lead to reduced economic efficiency. The high set-up times are mainly caused by the geometry adjustments which are necessary on the line for each forming stage to produce a profile which fulfills the tolerance requirements. There are many ways, how a roll forming line can be tuned to reach the desired profile geometry even with the identical tool set. This means there is no “right” or “wrong” set of machine parameters, which makes the detection of process failure based on in-process data even more challenging. The detection of success and failure produced by a parameter set is a crucial factor to rate the setup and can currently only be rated by the output geometry. There are a few approaches how to reduce these problems. Müller [67], Traub et al. [68], Lindgren [69], Leonhartsberger [70], Lamprecht [71] and a few others, already showed sensor integration into roll forming stands on a laboratory scale to investigate the process or to validate simulations. According to these publications, the integration of load cells into roll forming stands, to measure occurring contact normal forces is an efficient solution to monitor the process. Traub et al. in [72] even showed the integration of a sensory feather key to measure the torques on different tools. Another possibility to measure occurring load-levels via sensing bolts is demonstrated by Groche and Brenneis in [73]. However, most of these sensor integrations are used for research purposes. Commonly, the integration of such sensor equipment is not applicable in the industry in terms of costs, simply because an enormous number of roll forming stands is used in practise.

In the last decade, finite element (FE) simulations have become the state of the art instrument when the process of roll forming is studied. In most finite element models, the rolls are considered to be rigid bodies [74–79]. As a consequence, the emerging forming forces are independent of the compliance of the tools. The simulations can be used to identify the needed force levels to shape the bend radii of the desired profile correctly. The adjustments on a roll forming mill to get the desired shape are still carried out manually and directly in the arrangement on the roll forming line. These processes, needed to meet the given tolerance fields on the machine, are very time-consuming. Traub et al. in [68] showed a way to reduce the setup times for recurring profile shape/material combinations by monitoring the occurring forces and torques and assisting the operator to adjust the line until all monitored quantities are near the known reference (recorded before).

In contrast, this study focuses on the tuning process for “correct” adjustment of the rolling stands before production, ex ante, by using data from simulations or geometric features recorded from prior productions. Thereby no in-process sensors need to be used. The performance of the process is judged by installed sensors, which are just needed for validation.

4.1. EXAMPLE SETUP AND METHODOLOGY OF FORCE SENSING IN ROLL FORMING

In the course of these investigations, experiments with four forming passes were carried out to produce an unsymmetrical profile shown in Fig. 5 on the right side. All forming stages are equipped with force sensors (Kistler 9333A) integrated in the operator-side as well as the drive-side forming stands (Fig. 5 left). For detecting the output geometry, an automatic and laser-triangulation based scanning station (equipped with two Keyence LJ-V7200 - 2D Laser Profilers) is used to gather the 3D-data of every single profile during production.

For the reference measurement M_{ref} , the vertical positioning of the lower shafts remains unchanged, but the upper shaft is lowered until the load level of the corresponding simulation of the forming process with rigid and fixed forming rolls are established. This adjustment is then assessed by the output geometry of the profile, which is studied in detail to ensure its functionality. It could be revealed, that the force levels retrieved by simulations applied to the real process lead to sufficient profile geometry and a stable process. Further on, the measurement M_{ref} serves as the reference experiment to evaluate the functionality of the sensor assisted set-up process in comparison to the conventional. To validate the performance of the developed setup process, the profile geometry and arising forces are compared to the reproduction realized by different machine operators. The operators find a machine totally maladjusted and have to readjust it to generate the desired profile shape.

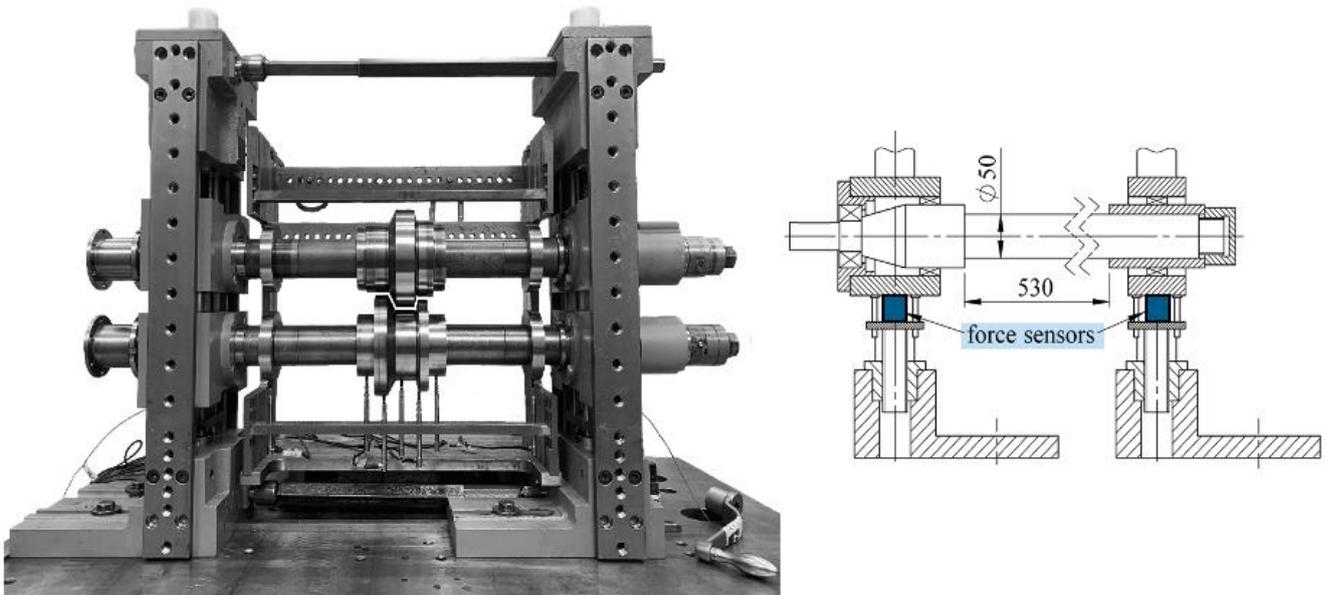


Fig. 5. Experimental setup and sensor integration

4.2. RESULTS OF SENSOR EQUIPPED ROLL FORMING PROCESS

Figure 6 shows the recorded contact normal forces in the forming stands and two corresponding characteristics of the output profile geometry derived from the 3D-data gathered by the mentioned scanning system. The different colors represent the forces recorded in the different forming stages of the profile. The grouped data is always one attempt to reproduce the reference state “ M_{ref} ”. The bar groups M_{O1} to M_{O4} show the reproduction of the machine operators by the conventional process without the usage of sensors. The other bar groups show the reproduction of the geometric characteristics recorded in M_{ref} by the described sensor assisted setup process.

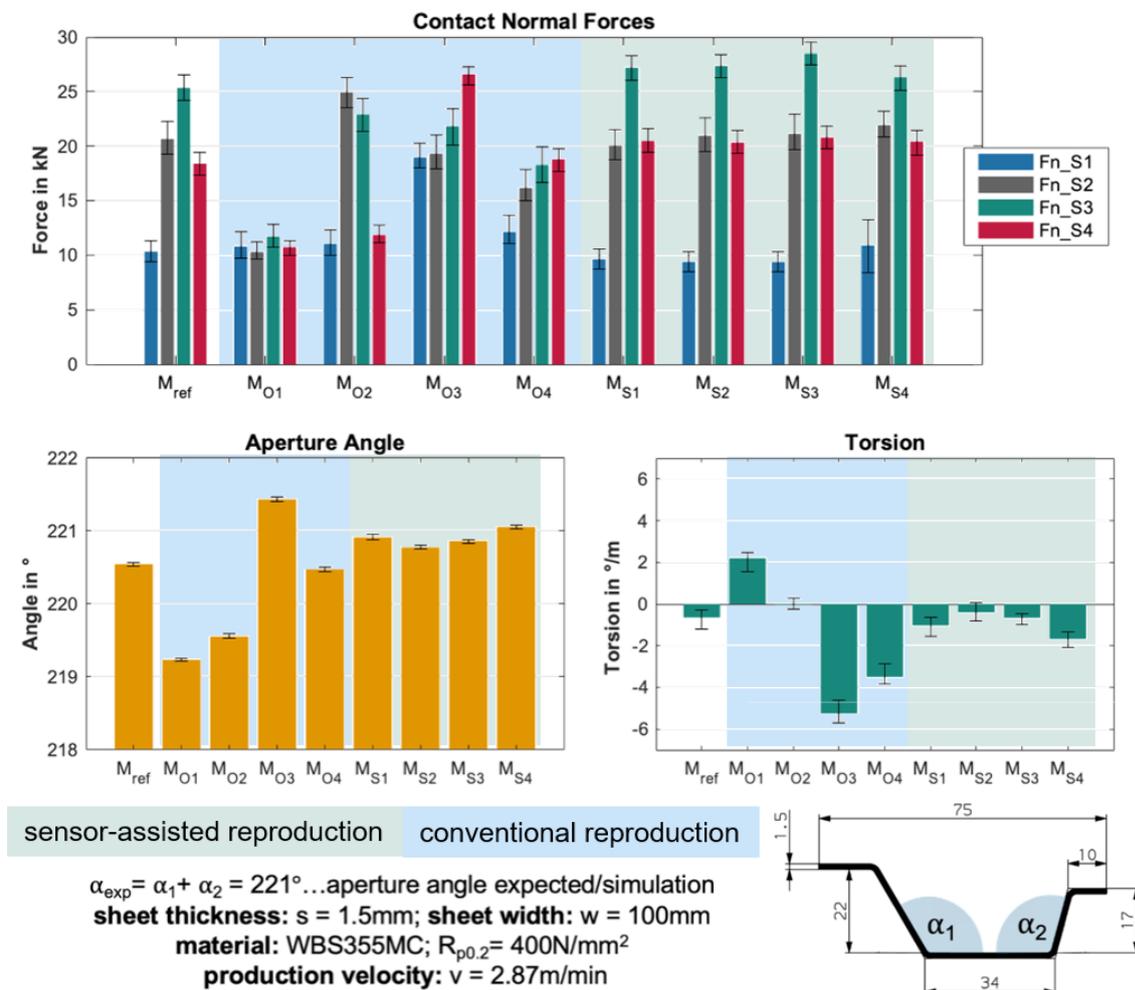


Fig. 6. Sensor equipped roll-forming leading to process stability

Comparing the conventional to the sensor assisted set up process, the scattering of the forces of the sensor-assisted process is way smaller, which leads to smaller variations in the geometry of the profile (see Fig. 6). The study shows the possibility of ensuring reproduction of line adjustments by the geometric state determined before and after

production in roll forming. Furthermore, the sensor assisted process generates a more stable profile geometry compared to the conventional process in several trials. This leads to the implementation of an inexpensive and robust adjustment processes without the necessity of the integration of sensors in the production line. The realization is implemented by the prediction of occurring forces by FE-simulations and adjusting the machines by geometric characteristics. Hereby, the changeover times of recurring profiles may be dramatically reduced. These experiments pave the way to establish simulation models of the process where integrated accurate tool behavior under load is considered. The digital replication of the machine can then be used to predict the needed geometric characteristics on a roll forming mill to reach the needed force-levels of the individual forming steps. The replica further on can be used to i.e. identify the influence of varying input quality of the metal sheet on the profile geometry.

5. HEAVY DUTY MILLING

Sensor integration into milling heads has been investigated in several research works and the already existing systems can be distinguished by way of data transmission. The measured cutting edge forces can be transmitted by a rotor system [80], near field communication [81] or via Bluetooth Low Energy [82].

Especially when milling large steel blocks, sensor integrated tooling systems are of great interest. Forging skin and oxide scale layers (Fig. 7) on the parts, as well as geometrical deviation and scattering material properties effect the process and cause varying conditions that easily effect process stability as shown by Dombovari [83]. Standardizing these stochastic conditions is impossible.



Fig. 7. Milling of big steel blocks with large scale milling heads

Monitoring real production processes near to the cutting edge by sensor integration into the tooling system raises certain challenges. In this particular use-case, usually no coolant is used for reasons of machinability [84] and so the temperature situation caused by the process has a much larger impact on the durability of sensors and electronics. Therefore, the integrated electronic parts need to be temperature resistant and shock or vibration proof, besides the problem on needed installation space.

Thus, an advanced approach with separated electronic circuits has been developed. The milling head gets equipped with temperature resistant electronics, but the battery, the telemetry system and acceleration measurement can be integrated into the adapter plate between the milling head and spindle. Thus, a new design was created combining the system of the instrumented tool holder with three PCBs (printed circuit boards) into one single PCB for integration into heavy duty milling machines, as shown in Fig. 8. The technology of the instrumented tool holder thus keeps its full functionality enhanced with the additional feature to deliver power supply and a transmission channel for a sensor integrated milling head conductively connected to the adapter plate.

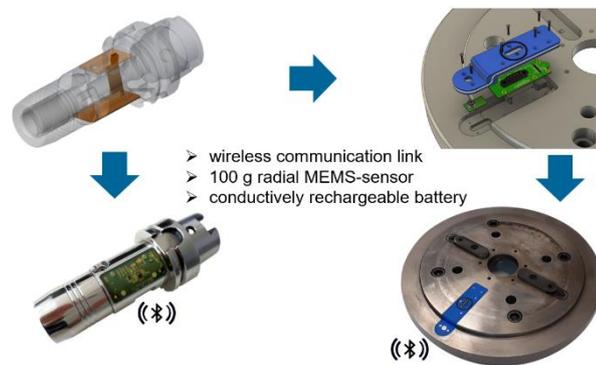


Fig. 8. Sensor integration into tool holder and adapter plate

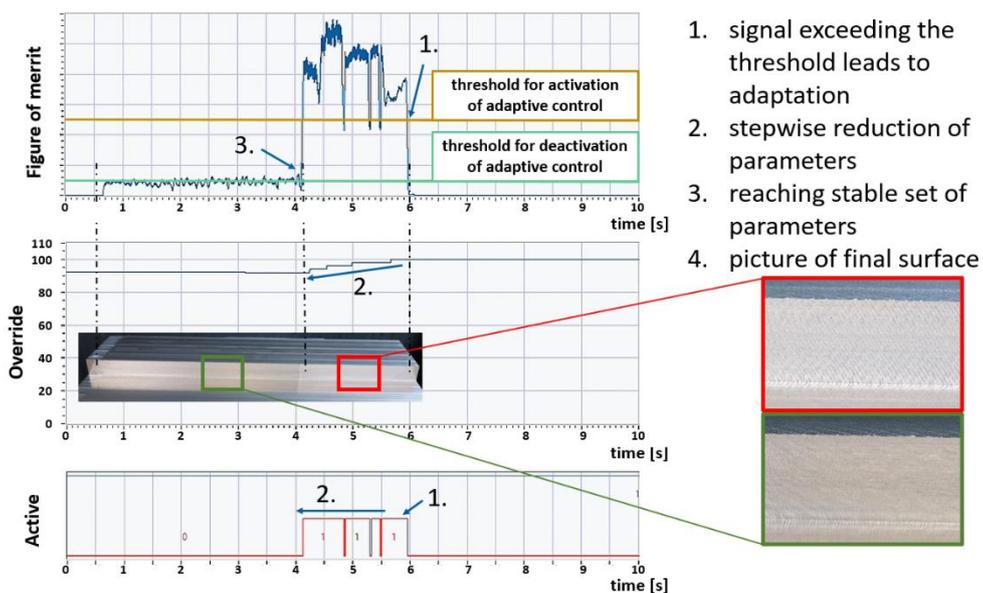


Fig. 9. Stabilizing milling process by real-time control based on sensor data

This design enables an additional data stream besides the acceleration data using the sensors, which can be located close to the cutting inserts. The sensory adapter plate transmits the gathered data to a stationary transceiver unit via a Bluetooth Low Energy communication channel. This transceiver uses a CAN interface to forward the data to a PC or special signal processing unit. The signal-processing unit provides possibilities for fast data analysis by a pre-defined algorithm and connection to networks or cloud services.

On the one hand, a fast and real-time rule engine sets counter-measures like adaption of spindle speed and feed rate via analog or digital inputs toward the NC-system of the machine tool. On the other hand, provision of data to the manufacturing executing level and sophisticated analyses become possible for not time-critical operations like long-term quality control and CAM based optimization of machining sequences.

A fast response and a specific adaption of the process are required for a feedback loop, so that a control system can cover stochastic process effects. The instrumented tool holder has been proven capable of chatter detection and mitigation [85, 86], as well as cutting edge chipping detection [87]. In the case, that a process is classified to be unstable, an automated adaption of spindle speed and feed rate can be applied in the real-time control loop. The use-case in Fig. 9 illustrates the effect of process adaption, however, a rather long distance of insufficient quality processed under unstable conditions remains. This procedure of extra-slow process adaption was chosen for reasons of demonstration and visualization. The adaptation of real production processes is executed much faster, resulting in sufficient quality over the whole work piece.

6. CONCLUSION

In this paper, applications and use-cases for sensor integration in tooling systems have been presented and an overview of the sensor data utilization has been provided. In order to achieve an optimum performance of manufacturing processes and complex production systems, time-related information has to be accessible and available from close to the area of the interaction between tool and work piece. Correlating the sensor's data with measurable physical properties of the produced parts is required for each application scenario individually to get a reliable statement or forecast regarding quality. Thus, sensor integration in tool systems enables economically valuable perspectives in different scenarios.

- Serial production processes can be monitored and a forecast of the quality of the products is possible, even if only a black-box model is used. The area of application in injection molding for example, enables to monitor the part quality regarding constant mass through the measurement of mold cavity pressure.
- Complex process models (white-box models) can be validated based on sensor data. Besides digital twins, quality assurance and reducing setup time based on sensor integration in tools have been presented by the use-case of roll forming. In this case, the integration of sensors will lead to deeper understanding of the process models. By their use to predict the processes forces, etc., extensive and thus costly sensor integration may be avoided in the industrial applications.

- Stochastic effects resulting from inhomogeneous work-piece material quality like oxide layer and forging skin in the case of heavy-duty milling take influence on the results of manufacturing processes. Real-time data evaluation of sensor information enables autonomous parameter adaption and therefore automated process control based on grey-box models.

Increasingly smaller parts of microelectronic components and the available communication technologies together with reducing prices will lead to even more sensor equipped production processes and components of machine tools. The increased quantity of sensor-based data allows for enhanced functionalities in the field of condition monitoring and quality control. Analysis and evaluating of sensor data will play a more and more crucial role. AI (artificial intelligence) and digital twins or process models, respectively, offer technologies to improve data exploration. A promising aspect can be derived from the use of new time sensitive networking capable technologies, which will allow for more complex evaluation methods and deploy further real-time capabilities.

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