Stamping Process Modelling in an Internet of Production

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Abstract

Sharing data between companies throughout the supply chain is expected to be beneficial for product quality as well as for the economical savings in the manufacturing industry. To utilize the available data in the vision of an Internet of Production (IoP) a precise condition monitoring of manufacturing and production processes that facilitates the quantification of influences throughout the supply chain is inevitable. In this paper, we consider stamping processes in the context of an Internet of Production and the preliminaries for analytical models that utilize the ever-increasing available data. Three research objectives to cope with the amount of data and for a methodology to monitor, analyze and evaluate the influence of available data onto stamping processes have been identified: (i) State detection based on cyclic sensor signals, (ii) mapping of in- and output parameter variations onto process states, and (iii) models for edge and in-network computing approaches. After discussing state-of-the-art approaches to monitor stamping processes and the introduction of the fineblanking process as an exemplary stamping process, a research roadmap for an IoP enabling modeling framework is presented.

Keywords: stamping process, industry 4.0, fineblanking, Internet of Production, condition monitoring, state detection

1. Introduction

Over the past decades, metal stamping technology has been replacing other metal forming processes such as forging and die-casting, caused by its low production time, costs, and the enhanced quality features [1]. Currently, around 20 % of car parts are manufactured using different stamping processes. According to a report by Grand View Research Inc. the global market for metal stamping is predicted to reach USD 299.6 billion by 2025 [2]. As a result to the quantities of produced workpieces, even a minor improvement in productivity, e.g., a few cents per workpiece, have a high economical influence. The increasing exchange of data throughout the supply chain, process control and the digitization have the potential to significantly lower the time to market and substantially grow the profit gains [3]. Hence, tools to model stamping processes are required to determine the influence of changing parameters in the supply chain onto the process and its outcome.

The vision of an Internet of Production (IoP) pursues enhancements in the area of production technology, both locally and globally [4]. While local improvements deal with measuring and storing all data sources and sensors to make them accessible to new means of context-aware analyses and may relate to traditional monitoring and embedded sensor approaches, the global improvements result from an interconnection of various data sources even from different stakeholders, effectively enabling (cross-domain) collaborations to utilize production technology advances on a large scale, i.e., in the complete IoP. For an IoP to turn into a reality, various research challenges still remain. On the one hand, the vast amount of (measurable) process

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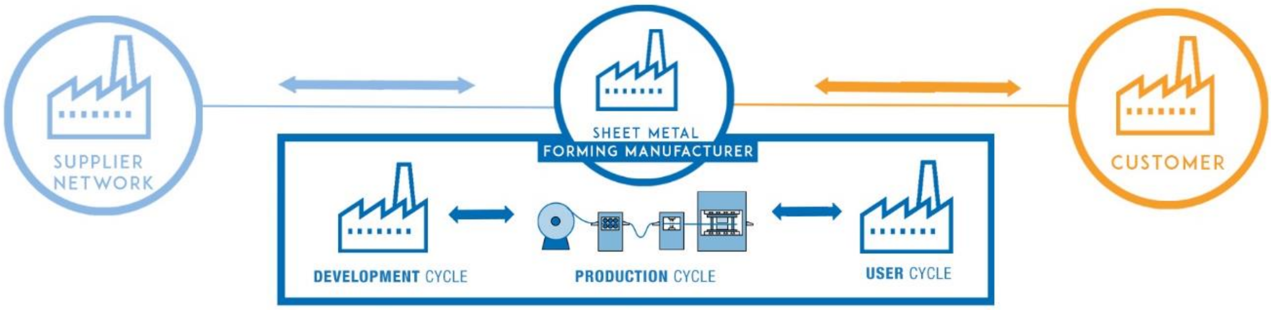

Figure 1: A schematic dataflow envisioned by the IoP can provide opportunities to manufacturers of different stakeholders. Suppliers of operational material, such as lubricant, material supplier or customer can be used to incorporate feedback data and adjust the process to reduce the necessity of secondary finishing processes. Additionally, data exchange between the different cycles of process development, production and usage cycle between several companies or within one company provides the potential to optimize processes and unravel new cause-effect relationships.

data overloads current infrastructures and does not scale with existing data models and storage systems [5]. Consequentially, mandating a careful selection of required process information which is highly valuable in subsequent analyses or control loops. Furthermore, the currently deployed infrastructure should be revised wrt. the capabilities of network resources and available cloud services. On the other hand, transferring company data (along the supply chain) is concerning from an information security perspective as control over valuable data in potentially untrusted environments is lost, while potentially revealing secret process information [6] or revealing communicating parties [7]. Therefore, the trade-off between the benefits of collaborating in an IoP and the precision requirements for shared process information must be analyzed meticulously. Given that these decisions must be reached in light of each specific application, no single overarching solution exists. However, new approaches also promise to enable privacy-preserving database requests even from remote knowledge databases [8]. Overall, significant research efforts are required to utilize the benefits in production technology as envisioned by an IoP.

Stamping is classified as one of the manufacturing operations in which shape, geometry, and physical properties are altered. Based on its principle, it is defined as a process in which thin-walled flat metal parts are shaped by punches and cutting dies to convert them into more complex three-dimensional pieces. According to the process parameters, such as the temperature, speed, deformation level and the desired product shapes, the stamping process can be categorized into different types such as deep drawing and blanking [9]. Similar to all the manufacturing processes, the mechanical degradation of the moving functional parts, the operating conditions, as well as the setup and human errors generate undeniable process inefficiency and produce inferior quality of the products. Downtimes due to corrupt process setups, machine failures or the usage of material that does not fit the tolerance of the process cause uneconomically usage of a stamping plant [10]. Hence, for an economically efficient usage of a plant, an effective monitoring system is a preliminary [11]. Whereas different stamping technologies have distinct differences in their technological foundation and mechanical effects, they also have undeniable similarities in terms of data analysis. Data acquired at the input of the process include continuous data of sheet metal properties, lubrication, and environmental factors, cyclic based sensor signals often acquired at the tool, such as forces or acoustic emission, and event-based data contained in control information of the machine. In the envisioned IoP, a monitoring system does not only take variations and degradations of elements into account, but also be able to use the vast amount of available abstract supply chain of different stakeholders and cross-domain data to effectively utilize the potentials of an IoP, see Figure 1.

In previous work, cyclic based sensor signals have been subject to various research that connecting variations to specific condition changes in the process [12]. Specifically, force and strain signals have been studied regarding its potential to monitor the underlying stamping process [13] so that signals and their extracted features have been linked to changing conditions in the context of different issues [14], namely, blank thickness changes [12], cushion pressure changes [15], slug at the tool [16] and workpiece failures [17].

Furthermore, it has been shown that the changes in lubrication and tool wear mechanisms can be detected by solely analyzing punch force variations [18]. A significant fraction of the product-to-product variation in the process can be predicted based on force measurements [19]. Tools that have been used to extract features of segments from the strain or force signals include principal component analysis [20], support vector machines [21], bispectral analysis [16], neural networks [22] and wavelet transformation [23]. During the analysis of these signals, approaches to break the strain or force signals into segments have been discussed, either based on different phases within the underlying forming process [23], or hierarchical splitting of the segments into smaller segments [24]. In the next step, the extracted features have been combined with unsupervised learning approaches, to classify force shape variations onto faulty states [25]. To predict the variations of punches in the future, Hidden Markov Models have been used to describe the dependencies between the punches [26].

Apart from the strain and force signals, acoustic emission and vibration have been studied extensively to detect wear, cracks or other faulty states during stamping processes [27] where vibration or audio sensors imply high frequencies. It has been shown that features of vibration signals are linked to various changing input parameters such as blank misfeed or thickness [28]. By using vibration signals in the piercing process, a logistic regression model estimates the tool condition and detects punch breakage with an accuracy of up to 99 % [29]. Furthermore, acoustic emission signals can be used to detect cracks in e.g., automotive stamping processes [30], identifying the progression of wear [31] and have been studied in terms of sound-based event detection in the sheet metal stamping [32]. In summary, the analysis of cyclic force, strain, acoustic emission and vibration signals of stamping processes contains rich information about the defects of products and state changes of the process which is a preliminary to use these signals in an effective monitoring system. Therefore, implementing an advanced state detection methodology based on cyclic sensor data variations offers high potential to capture occurring condition changes in detail, which is the foundation for an IoP enabled monitoring system.

In this paper, the focus is set on identifying research objectives to analyze stamping processes in context of an IoP by investigating particularly the fineblanking process as the case study. In the next section, a detailed description of the identified research objectives that enable the integration of sheet metal stamping processes into an IoP is stated and discussed. Next, in Section 3, the experimental and data acquisition setup at the research facility's shop floor that allows the pursuit of the research objectives in an industrial context is given. Eventually, a conclusion of the proposed research challenges is presented in Section 4.

2. Stamping processes in an Internet of Production

The vision of an Internet of Production describes that data and information are exchanged between the product development, production and usage cycle, as well as between companies alongside the supply chain. The providers of the coil material used in a stamping process gets feedback information about the performance of the coil during the process which grants them a larger dataset to optimize their product quality. On the other hand, the coil material supplier can provide manufacturers with detailed information about material properties for each position on the coil, so that manufactures can setup their process, accordingly, leading to fewer amounts of produced scrap or wear at the tool. In addition, data from customers about the performance of individual workpieces can be correlated with process parameter setups in the manufacturing process, effectively enabling the optimization of the process based on real feedback data on a per workpiece basis. Since, from a data point of view, all stamping processes have continuous input, cyclic based data regarding the punch and often event data for influences or machine control information, models that connect the different data sources derived by the study of a specific stamping process have the potential to be generalizable for other stamping processes.

Practically, in stamping processes each punch cycle shows variations in the cycle-based force measurement signal [18] and quality features vary within certain boundaries [33] due to changing input condition of the process, e.g., fluctuating material properties of the sheet metal [34]. Thus, the outcome is changing continuously with the input, while the process setup remains unchanged [19]. To understand the interconnection between the fluctuations within the signals themselves, changing input parameters and the quality features can be identified as one of the most important goals to achieve, since it allows the mapping

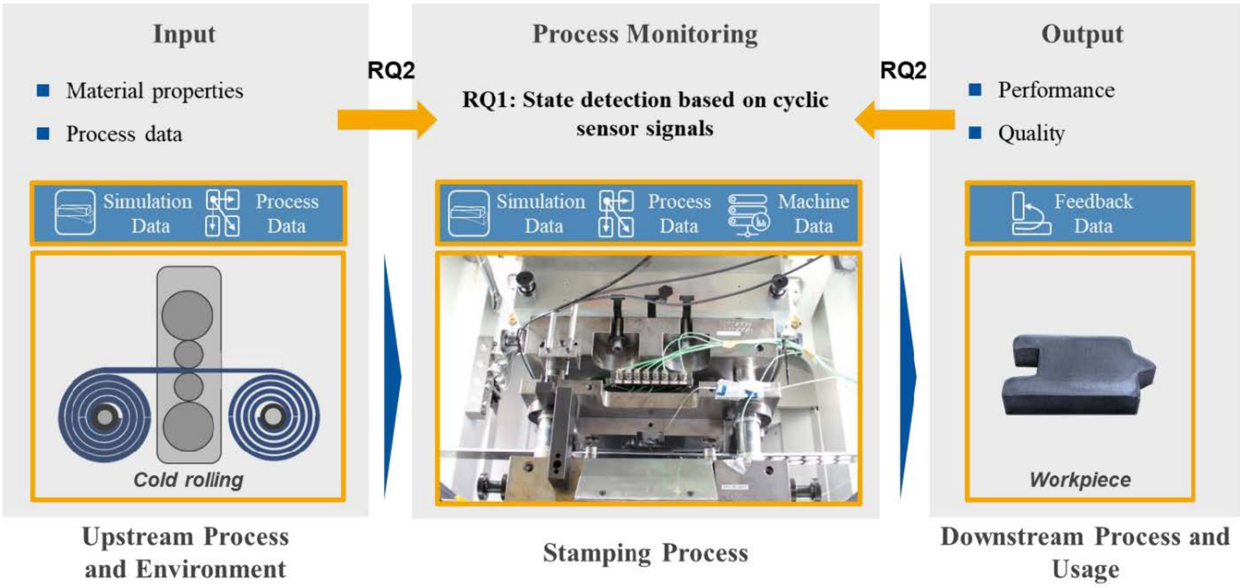

Figure 2: The goal for a holistic stamping process modelling is that the available data from upstream and downstream processes can be mapped onto anomalies, states and events detected during the process execution. In this figure, rolling as an example upstream process and a workpiece that represents a set of characteristic geometries is illustrated. The first research question (RQ1) considers the detailed process monitoring of blanking itself, where the second research question 2 (RQ2) focuses on mapping the output and input onto anomalies and events detected in the process monitoring. The third research question deals with the embedding of the approaches into edge and in-network approaches [5] to reduce and handle the amount of produced data.

of (e.g., changes higher up in the supply chain) onto the process and its quality outcome. Additionally, adequate approaches to store and process the vast amounts of data created during the process [5] has to be taken into account. To this end, three main obstacles have to be addressed, see Figure 2: (i) State detection based on cyclic sensor signals, (ii) mapping of in- and output parameter variations onto process states, and (iii) models for edge and in-network computing approaches.

State detection based on cyclic sensor signals: For every punch, each sensor signal has a characteristic shape, with slight variations both regularly and irregularly, in Figure 3 data of an exemplary fineblanking punch is presented. Based on the variations of an assumed stable process, each punch (or a series of punches) can be associated to a particular state. A state, in this context, is defined as a representation of a particular condition of the process that does not necessarily has to be known. The state is determined based on a distinguished set of current sensors' signal shapes and features, whereas a state change indicates a change in the sensor signals' feature set that may relate to changes in the underlying physical process. As a result, data of a stamping process can be discretized wrt. punches and a series of punches can be classified into a series of states, with each state distinguished from another one by a, possibly unknown, change in condition. Various researchers have proven that features of acoustic emission and force signals are independently linked to different conditions of the underlying forming process, cf. Section 1. Thus, an analysis of the combined feature space of all the different cyclic sensor signals together has a high potential. Advanced monitoring approaches for manufacturing processes already sketched detailed pipelines to monitor state changes of the underlying manufacturing process [35], see Figure 4. Raw signals can be decomposed into individual components, e.g., frequency components with DWT [36], features are extracted, selected [37] and eventually, reduced to the desired number of signals to train predictive models [38]. For manufacturing processes, it is unrealistic to have a sufficient amount of labelled sensor signal events for all condition changes [38]. As a result, in a next step the unsupervised detection of state changes within the derived feature space during the process based on all available sensor data is essential to effectively monitor and track the behavior of stamping processes.

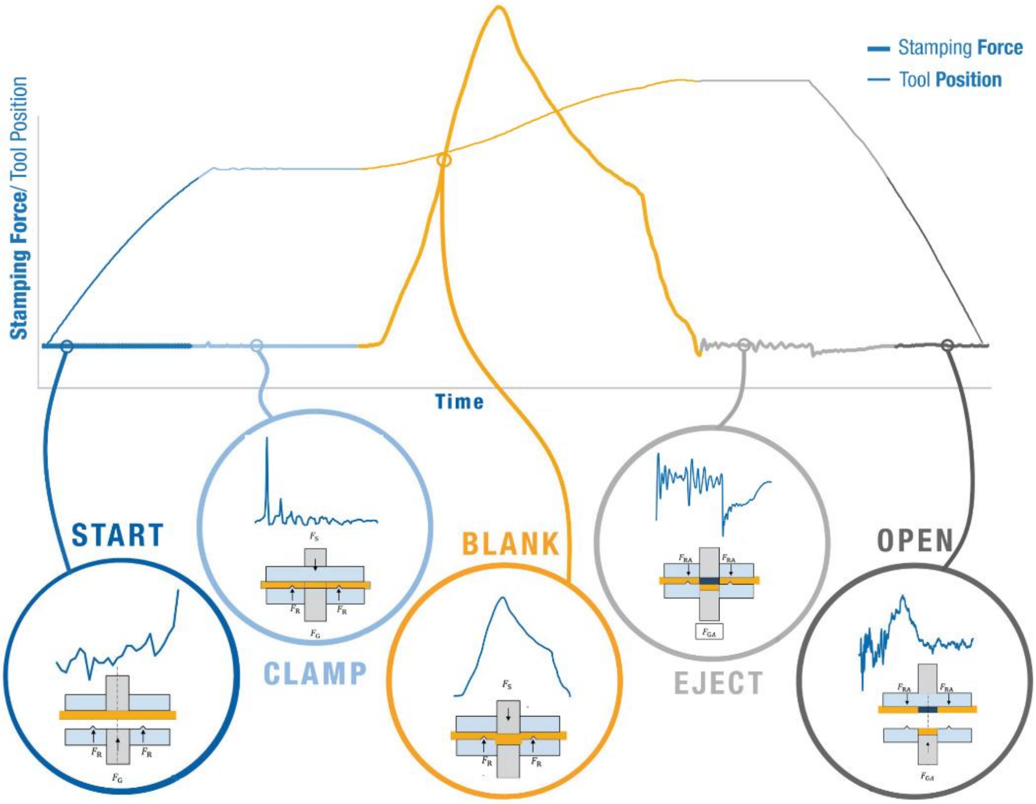

Figure 3: The force and stroke signals represent characteristic process signature. For a detailed analysis, the signals can be decomposed into three logical segments regarding the clamping of the sheet metal, execution of the blanking process and ejection of the punch out of the sheet metal.

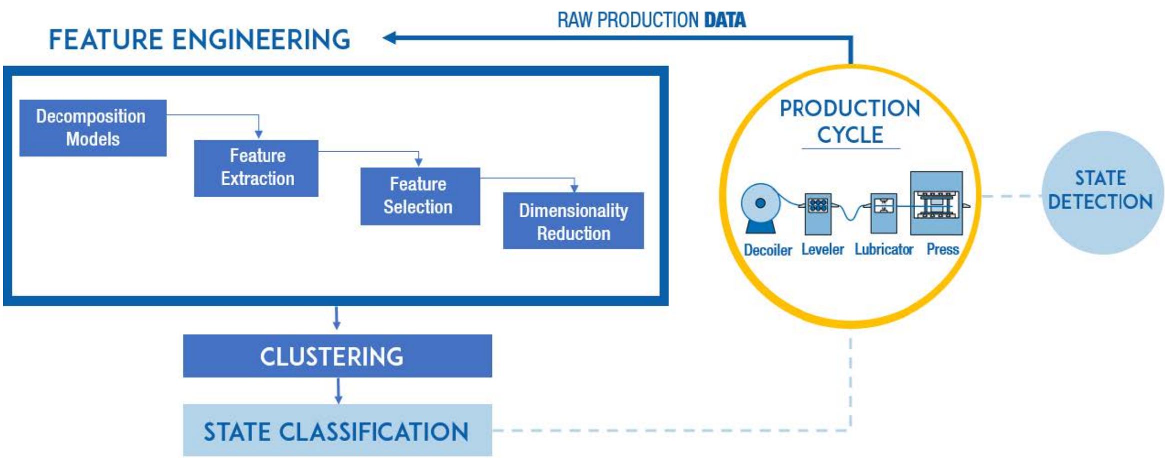

Figure 4: A common pipeline for unlabeled state detection can consists of different steps [33]. Raw data is acquired at the process and processed by decomposing the signal into its components, e.g., frequency components, extracting features, selection features and reducing the dimensionality of the features. All steps can be either skipped or combined; the outcome is then used for a clustering to find similar patterns.

Mapping of in- and output parameter variations onto process states: Based on the acquired sensor data of the in- and output of the machine, the detected conditions have to be linked to physical condition changes that influences the process, e.g., changes in the tribological system of the process influenced by surface roughness or lubricant. This data provides valuable information about the cause of variations in sensor signals measured at the tool and their effect onto the outcome of the process, namely, the quality features of the workpieces. Technically, these questions relate to the classical supervised learning applications. Given the input parameters, such as hardness condition of the material, roughness of the surface, temperature, vibration and humidity of the environment, and the label, namely the state, it is to predict the state or state changes that will occur in the process. At the same time, given output parameters like the die roll or shearing surface quality, the goal is to connect the derived states with these output parameters enabling their prediction. The same techniques can also be used to predict future developments of process conditions based on the current state and features of sensor signals derived by the current punch [26]. These Hidden Markov Models provide an appropriate framework for modelling of manufacturing process in general, and need to be adapted for the usage in stamping processes. The necessity for these models and questions motivated the experimental setup described in Section 3 that allows the tracking of various input parameters. A future challenge is measuring quality features online so that the full dataset not only contains input information, but also the output information of every single punch, allowing to directly correlate condition changes onto the quality features of interest. Eventually, this enables not only to quantify the influence of effects onto the process, but also allows to identify new cause-effect relationships and parameter setup optimization.

Models for edge and in-network computing approaches: Depending on the types of used sensors and their concrete configuration, the overall amount of data collected at the fineblanking machine can easily surpass 6 Gbit/s [5]. Storing such amounts of data on local storage platforms is not feasible; outsourcing the data to off-premise clouds is not a viable option either as typical Internet access speeds are insufficient. Besides, privacy risks of cloud services have been studied [39], revealing an entanglement and opaqueness of different cloud providers, i.e., exposing sensitive information to third parties. In this regard, a joint architecture which makes use of edge, in-network and cloud computing approaches offers a very promising starting point, especially if it purposefully combines the advantages of the different concepts [5]. By performing computations and analysis steps as close to the source of data as possible, the amount of transmitted data can effectively be reduced. Simple filtering mechanisms are for example a viable option if the transmission frequency of the sensors cannot be configured and is higher than needed. In this case, in-network filters placed on general networking devices, such as switches, can shape down the transmission frequency, preventing a network overload. With growing complexity, either operations can be placed on edge or ultimately on cloud computing platforms, although placing them further away from the data sources diminishes their positive effect [40]. Apart from improving the data collection and analysis mechanisms, the proposed architecture can also support the control of the physical processes which underlie the forming process. Such processes are typically subject to tight latency constraints as e.g., punching can result in over 1000 punches per minute, which is why the control is performed on dedicated PLC controllers in close vicinity to the controlled machines. The PLCs are limited in their computational capabilities and cannot be used for more complex control loops. A joint architecture that distributes parts of the control functionality on the different available components, e.g., simple versions on in-network devices for a fast response time while more complex versions can be placed on edge or cloud platforms [41], could offer a viable solution, but the coordination between the different components is yet not well-researched. To this end, the proposed research group COIN of the IRTF is working on exploring the continuum between in-network, edge and cloud computing. Hereby, identifying guidelines as to where to place which function is especially important.

3. An Internet of Production-enabled fineblanking line

To develop methods and models for stamping operations an authentic experimental setup that represents conditions in a mass production environment, especially wrt. the number of produced workpieces is required. Hence, fineblanking is regarded as an exemplary process for data generation and the developing methodologies. Blanking processes are one of the most important stamping processes in the industry, where the incoming material is sheared to the desired shape. To overcome the defects coming from the process design the process have been developed to hot blanking, high-speed blanking, and fineblanking [42].

3.1. The production line

Fineblanking is a precision forming process for producing functional metal components with smooth-sheared edges over the entire workpiece in just one-step forming action with a small die clearance compared to conventional blanking [43]. While the conventional blanking tool is composed from two main parts, the punch and the die, the fineblanking tool is more advanced and contains two additional parts, the blank holder and the counterpunch [42]. These special tool designs affect the material flow characteristics, so that the deformation in fineblanking process is more violent and localized than in conventional blanking [44].

Despite the relatively good workpiece quality, qualitative defects of the fineblanked components can impair their functionality. Thus, the uncertainties that prevail in the manufacture of fineblanked components are not identical and require expensive secondary finishing steps, e.g., grinding, to achieve quality features accuracy with respect to surface topography, dimensions and geometry. In a typical setup, first, a decoiler unrolls the raw material, which is usually a 1–20 mm thick and 50–250 mm wide metal coil. The decoiled sheet is then fed into a leveler to relieve the residual stresses as far as possible [9]. Eventually, before the actual fineblanking process takes place in the press, a lubricant film is applied on the metal sheet, which is then cut by the tool of the press.

The specific equipment of the fineblanking line consists of a coil system that feeds the coil into the straightener from ARKU and advances the coil to the servo-mechanical Feintool XFT 2500 Speed fineblanking press with a lubrication system from TechnoTrans. The press can be configured to run with a speedup of up to 140 strokes/min.

3.2. Data acquisition

The fineblanking line located at the research institute is subjected to research experiments and has been equipped with 21 additional sensors to monitor process parameters during the blanking process execution. Executed experiments include lubricant, material, punch-alloy and punch material variations as well as variations in the process setup such as speed, where in most experimental setups several thousand punching operations are performed.

Machine: The SPS-bus system of the fineblanking line is used to exchange a reduced process image between the decoiler, leveler, lubricator and press, but also for components inside the press itself. The data gathered at the SPS-bus system are sampled with a frequency of 2.5 kHz and contain time series data about power consumption, state information of different machine components as well as build-in sensor signals such as punch acceleration, temperature or hydraulic pressure sensors. Tool: The tool has been modified to allow the measurement of forces applied onto the components of the tool, see Figure 5. The punch (x4), counter punch (x1) and blank holder (x4) forces are measured redundantly to ensure precision of measured forces. Furthermore, four piezoelectric bolts measure peripheral forces applied onto the tool during the process. The acceleration and stroke of both the punch and counterpunch, as well as all force sensors, are sampled with 10 kHz and acquired via an additional measuring system independent of the SPS-bus system. Exemplary stroke and force measurements for one punch measured at the tool is presented in Figure 3.

Material: The properties of the material and its surface are critical for the outcome of the fineblanking process [45]. Unfortunately, these properties are fluctuating within a certain tolerance given by the manufacturer [35]. To correlate deviations in the force signals with changes in the input to the process it is necessary to measure those properties inline. In the described setup a sensor system to measure the roughness of the surface, a system to measure the thickness of the coil and a sensor system based on the effects of magnetic barkhausen noise for hardness conditions [46], are used to measure incoming material properties.

Quality Features: The quality features of the workpiece, mainly the die roll at all positions of interest is acquired by scanning it with GOM ATOS optical measurement system [47] to generate the 3D model of the workpiece.

Environment: To measure other factors of the environment that influences the outcome of the process sensors for humidity, temperature, air pressure and vibration have been applied onto the tool as well as outside onto the machine. In summary, the sensory equipment can acquire data containing information about

Figure 5: The fineblanking tool displayed is equipped with various sensors to acquire sensitive process information. All the information generated by the sensors in the above figure are not transferred via the SPS-bus system, but acquired with additional measuring equipment.

the input of the process including material and surface properties as well as environmental conditions, information about the machine itself via the SPS-signals, process execution and output of the process. Together with the heterogeneity of executed experiments, an analysis and comprehensive data driven understanding of the process itself and its direct influences can effectively be conducted using the described process setup.

4. Conclusion

The availability of data shared between companies along the supply chain as well as across stakeholders and product domains as envisioned by an Internet of Production (IoP) can contribute to reduce costs, improve quality and increase profit margins in manufacturing companies. To make use of the increasing availability of data in a production environment, it is essential to enable companies to quantify external influences onto their manufacturing process as well as predicting the expected outcome to give valuable feedback to suppliers and domains regarding their product quality. Where in existing condition monitoring approaches state changes of stamping processes are based on the analysis of single sensor signals, new holistic models that utilize multiple sensor signals are needed to capture a complete state of the process at a given time.

In this paper, the modelling of stamping processes in general, and specifically of a fineblanking line, is discussed and three main research objectives are identified: (i) State detection based on cyclic sensor signals, (ii) mapping of in- and output parameter variations onto process states, and (iii) models for edge and in-network computing approaches. Given the experimental setup described in this paper, the research objectives will be studied using the data of various research experiments executed on the stamping machine. Especially, the high frequency, quantity and heterogeneity of the acquired data allow to conduct studies on the performance of different methods to detect state changes in the forming process that have not been recognized before. Datasets containing input data for the process, sensor signals of the process itself, wear progression of tool elements and variations of quality measures of the resulting work pieces allow not only to fully decompose the process into different states but also the development of analytical models that enable manufacturers to use the data available in an envisioned Internet of Production.

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