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PROCESSES

Softsensors: key component of property control in forming technology

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Abstract
The constantly increasing challenges of production technology for the economic and resource-saving production of metallic workpieces require, among other things, the optimisation of existing processes. Forming technology, which is confronted with new challenges regarding the quality of the workpieces, must also organise the individual processes more efficiently and at the same time more reliably in order to be able to guarantee good workpiece quality and at the same time to be able to produce economically. One way to meet these challenges is to carry out the forming processes in closed-loop control systems using softsensors. Despite the many potential applications of softsensors in the field of forming technology, there is still no definition of the term softsensor. This publication therefore proposes a definition of the softsensor based on the definition of a sensor and the distinction from the observer, which on the one hand is intended to stimulate scientific discourse and on the other hand is also intended to form the basis for further scientific work. Based on this definition, a wide variety of highly topical application examples of various softsensors in the field of forming technology are given.

Keywords Forming · Process control · Softsensor · Observer

1 Introduction

Mechanical and industrial engineering, and in particular transport technology, are important markets for metallic workpieces with high demands on specific properties such as strength, reliability and geometry accuracy. These workpieces can often be produced advantageously using forming technology. However, increasing demands on properties (like the specific strength) as well as economic and social conditions mean that the efficiency and sustainability of manufacturing technology are gaining in importance. As a result, the efficiency, reliability and process safety of the underlying production processes must increase. A possible approach to this in the area of forming processes is the reduction of required safety distances to process limits by executing the manufacturing process within closed-loop control systems using sensors to gain necessary process information.

In general (cross-disciplinary), the term sensor is used to describe a device which detects or measures (physical) properties or changes and provides a corresponding output or measurement in response [1]. Different types of sensors are used. The physical sensor is defined as a sensor that responds to a physical stimulus (e.g., temperature or pressure) and converts it into a resulting pulse, which is often an electrical signal [2]. A virtual sensor is a (software) sensor with greater freedom of application compared to the physical limitations of classic sensors that independently and autonomously generates an output signal based on the combination and aggregation of input signals (e.g. from physical sensors) [3]. In addition to these two sensor types, the softsensor is

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also frequently used and is described and defined below. In the area of process engineering, it is e.g. defined that a softsensor consists of a combination of real sensors or arrays of measured values and mathematical approaches/models for correlating measurable parameters of a process and control variables that are difficult or impossible to measure [4]. Especially in complex control systems (e.g. in process engineering), with for example, a large number of measured variables to be processed, softsensors can be very attractive, not only economically [5]. Besides production technology, softsensors are also used in forming technology due to their many advantages [6]. The objectives of the application of softsensors in process engineering here include error detection and compensation by equalising drift, outliers and noise or improving the description of the process state through "multivariate features". This improves accuracy, safety and error detection and compensation. Furthermore, multi-point measurement can be implemented, which is mostly accompanied by data-based approaches [6].

In the area of forming technology, due to the complex (and multi-stage) processes, relevant and central input variables are often missing in order to be able to build up an efficient process control. Here the use of softsensors represents a significant improvement. The application of softsensors in the area of forming technology is therefore often pursued with the aim of improving workpiece quality as well as stabilising forming processes to the point where they become reproducible in the first place. There is a multitude of application examples for the use of softsensors in the field of forming technology, some of which are explained later in this publication. Despite these many applications, a definition of a softsensor used in forming-oriented property control is still missing. Since such a clear definition of the term is the basis for targeted scientific research and discussion, one of the aims of this paper is to stimulate a scientific discussion on the use and impact of softsensors in forming technology and especially in connection with property control by trying to define important terms, identify areas of application and give examples.

2 Definition of sensor, softsensor and observer

The following definitions and explanations were worked out in the Forming Technology Working Group of the DFG Priority Programme 2183:

2.1 Sensor

A sensor generates an output signal based on causal relationships in the presence of an input signal. The causality is established by a process-independent model, so that no application-specific domain knowledge comes into consideration. Thus, a sensor can also be applied in a process-independent manner.

2.2 Softsensor

The softsensor (Fig. 1) supplements the sensor with application-specific domain knowledge and processes incoming physical or digital sensor signals. The causality between input and output variables is established by a process-specific model (white, gray or black), which necessarily requires current process information. Analytical equations, differential equations, characteristic diagrams, data-based models or simulations such as FEA can be used (Fig. 2a–c). Furthermore, the model must have a dependence on the process time

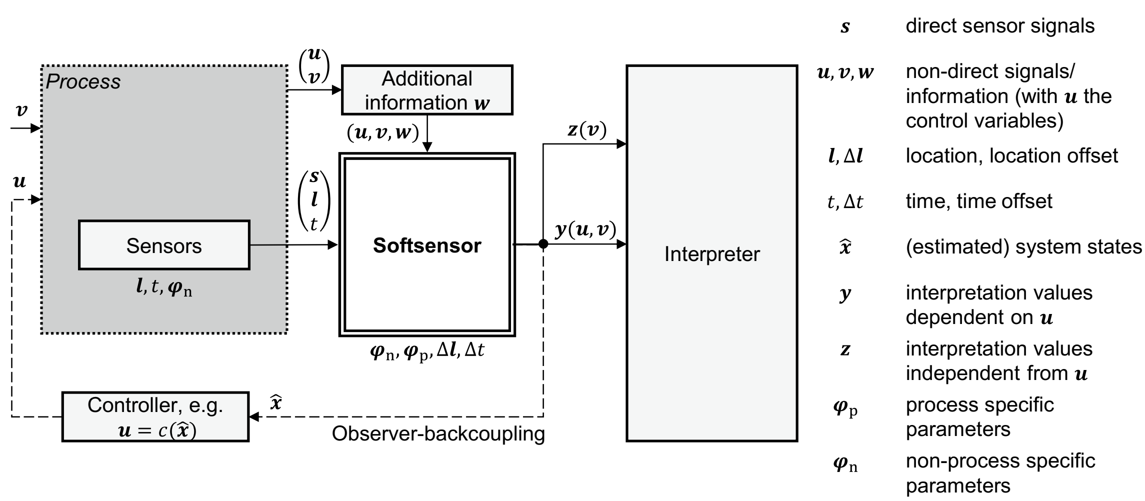

Fig. 1 Overview softsensordesign

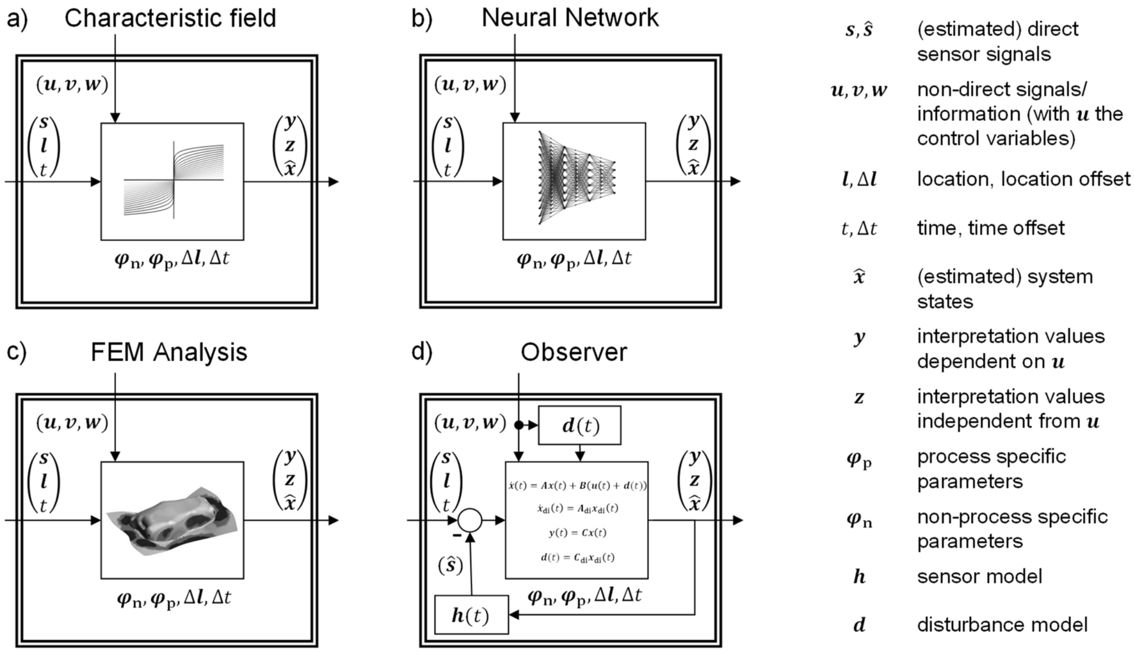

Fig. 2 Model types for softsensors (**a**–**c**) and observers (**d**)

and/or the considered location and must allow an interpolation or extrapolation.

2.3 Observer

The observer (Fig. 2d) represents a special form of the softsensor, in which the process-specific model is supplemented by a (mathematical) model of the physical (real) sensors (hereafter observer output) and a feedback is generated with it. In the simplest case, the latter is based on the evaluation of the difference between the sensor signals of the process with the output signals generated by the observer and their suitably weighted feedback into the observer equations. This correction step generates a continuous adaptation of the observed quantities to the current process state with the aim of asymptotically stabilizing the observer error or minimizing its expected value. One example of the use of an observer is the electronic stability program (esp) in a car to monitor the vehicle's system state [7].

3 Application of softsensors in metal forming

3.1 Examples for process and property control

In the previous sections, the paper aimed at defining the topic of softsensor concepts. The following section contains a review of different application examples for softsensors. These examples can be classified by the type of application, the motivation to apply a softsensor, the physical sensor part and the underlying softsensor model, that transforms the measurement value of one or more physical sensor $X_{i,M}$ into the softsensor signal X_j. The variable used here for the value of one or more physical sensors describes in this case the total amount of the different input variables described in Figs. 1 and 2.

$$X_j = f(X_{i,M}) \tag{1}$$

In each application the physical measurement quantity (softsensor input) is chosen considering the process characteristics and the workpiece material. For example, Barkhausen noise measurements could only be used for softsensors in processes with magnetic workpieces, and humidity measurements are of interest for hygroscopic materials such as paperboard. The measurement of workpiece displacements perpendicular to the direction of the acting process forces can be highly relevant (as in deep drawing) or superfluous (as in extrusion).

Softsensors are advantageous when either the softsensor cannot be measured directly in the specific process, or when the cost of measuring the softsensor input and the softsensor itself is lower compared to direct measurement. The chosen physical measurement quantity should have a distinct physical or statistical correlation to the sought softsensor signal. Thus, the measurement values for softsensors differ in the various applications (see Table 1).

Table 1 Overview of different softsensor applications

Use case	Measurement value X_M	Softsensor signal X_j
Flat rolling	Input strip width	Roughness inside the rolling gap
	Roll force	
Ring rolling	Surface temperature	Hardness within the bulk
	Ring size	
	Tool position	
Punch-hole rolling	Magnetic Barkhausen noise	α'-martensite fraction
Flow forming with α'-martensite content control	Magnetic Barkhausen noise	α'-martensite fraction
Flow forming with strain hardening control	Magnetic permeability	Work hardening
	Magnetic anisotropy	
	Temperature	
Multi-stage hot sheet metal forming process	Temperature	Hardness
		Yield stress
Incremental sheet forming (ISF)	Shape	Step depth
		Step size
Progressive die bending	Two distances measured with laser sensors (s1, s2)	Springback angle
Blanking	Force	Wear state

The requirements for the output signal of a softsensor in a certain use case depend—besides the process, the materials, and the measurable quantities—also on the specific purpose of the softsensor. Relevant purposes include the feedback signal for a controller in a process or property closed-loop control and the monitoring of a tool or process condition. Softsensors also allow redundancy to signals from physical sensors or other softsensors. This is particularly exploited in fault diagnoses and reliability analyses.

3.1.1 Process and property control

The main function of softsensors in process and property controls is to derive a feedback signal for the controller. This particularly implies the determination of workpiece or process conditions in real time. For this reason, softsensors in control architectures require both non-destructive testing methods for the physical sensor and real-time capable softsensor models for the virtual part. The operational area of softsensors in process and property controls is versatile and covers the entire range of metal forming processes.

3.1.2 Flat rolling

In [8, 9], Schulte et. al. have developed a process control for the concluding skin-pass rolling process step in a cold rolling process chain. In this process stage, the properties of the resulting forming parts, in particular the surface surface roughness *Ra* and thus tribological property [10], paintability, and paint gloss, can be adjusted. Experimental tests were conducted using a conventional duo roll stand equipped with textured work rolls. During the process, the metal strip is pulled through the rolling gap, which is accompanied by a strip's thickness reduction due to the acting forming forces. Skin-pass rolling differs from conventional cold rolling steps by textured roll surfaces that allow a defined surface roughness on the strip, and by lower forming forces, which mitigate thickness reduction. Additionally, a new actuator, strip tension (Z_0, Z_1), is also introduced to add extra flexibility and to decouple the thickness reduction and resulting surface roughness [11]. This principle is extended in [8] by a model predictive control to ensure the desired surface roughness and strip thickness despite process disturbances. For this purpose, the surface roughness has to be determined online in the forming process. Since conventional sensors cannot be placed directly in the forming zone for geometric reasons, a novel, contactless roughness sensor is installed after the rolling gap. However, this leads to an undesired dead time between forming operation and measurement. Schulte et al. propose a softsensor approach to counter this disadvantage. Here, the roughness in the roll gap is calculated depending on the measured force and the incoming strip width by an adaptive grey-box model. As a peculiarity, the model parameters are continuously identified and modified by a Gaussian process regression algorithm (GPR) online during the process based on the conventional roughness measurements carried out outside the gap. In Fig. 3, the process, relevant process parameters, and measurement applications are shown. The surface roughness in the gap as softsensor output is marked by a frame with a dashed line. The physical parts of the softsensor are highlighted

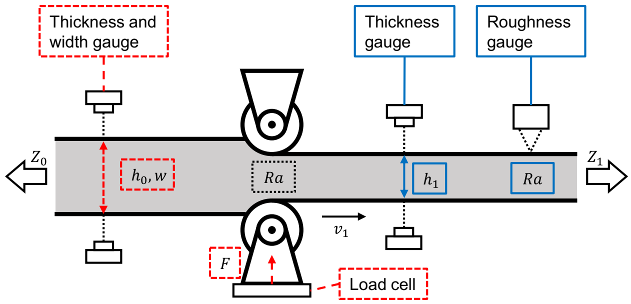

Fig. 3 Sensor concept for property controlled flat rolling, adapted by [8]

with a dashed red frame. Further sensors are shown with a blue frame and their measured values are written in italics.

3.1.3 Ring rolling

Model predictive control and softsensor strategies were also proposed for tangential profile ring rolling (TPRR) in [12]. In this process, an annular semifinished part mounted on a mandrel is deformed by a rotating roller which is driven towards the roll with a defined velocity (Fig. 4). This increases the diameter of the ring. In [12], thermomechanical TPRR is used with preheated semifinished parts cooled with compressive air during forming. This process affects the geometry of the forming part as well as the microstructure, grain size and dislocation density. Lafarage et al. therefore aim to establish a control for the hardness of the workpiece at the end of the process by predicting the optimum starting temperature, cooling rate and roll speed. Since the hardness in the mass of the workpiece as a feedback variable of the control cannot be measured directly online without destructive testing methods, a softsensor for determining the hardness is proposed in [12]. The softsensor input consists of the measured surface temperature (that is correlated to the inner temperature), the tool position and the ring size, as well as additional information from the control schedule. A hybrid approach is used for the softsensor model, which consists of three submodels: a thermal model, a deformation model, and a microstructure model. The plastic deformation is calculated by a deep neural network (DNN), the thermal model consists of an exponential, time-depending cooling curve and for the concluding determination of the softsensor output a dynamic recrystallization model is used.

3.1.4 Punch-hole rolling

An approach for online determination of the α’-martensite volume fraction is proposed in [13] for a punch-hole rolling process (Fig. 5). The novel process consists of two process steps: shear cutting and rolling [14]. At first, conventional punching is used for manufacturing a hole in a blank. In the second step, the hole is widened by the rolling process. For this purpose, the die is removed from the contact zone. This enables a superimposed, helical toolpath consisting of a rotation of the punch perpendicular to the hole and an additional tool movement (feed) in radial direction. In current research, the rolling process step is aided by a closed-loop control approach to ensure the desired product geometry and properties despite process disturbances such as variations in the semifinished products. Thus, a softsensor is used to determine the controller feedback from the magnetic Barkhausen noise measured by a micromagnetic Stresstech sensor [13]. For austenitic stainless steel blanks, this softsensor is used to calculate the α’-martensite volume fraction.

3.1.5 Flow forming with α′-martensite content control

Flow forming is used for forming rotationally symmetric parts in small batch sizes. The production of parts with complex geometry and locally graded, defined material properties depicts a great challenge for the current forming process due to the large number of disturbance variables and phase

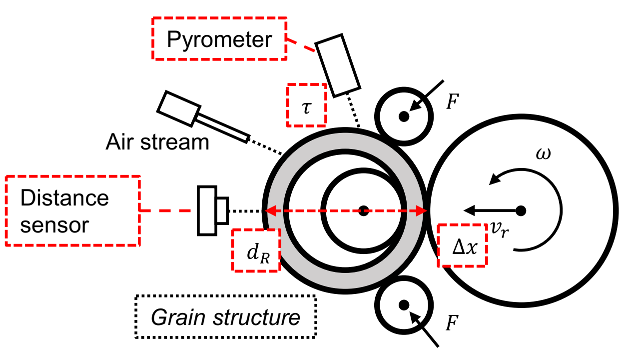

Fig. 4 Ring rolling process design and softsensor approach, adapted by [12]

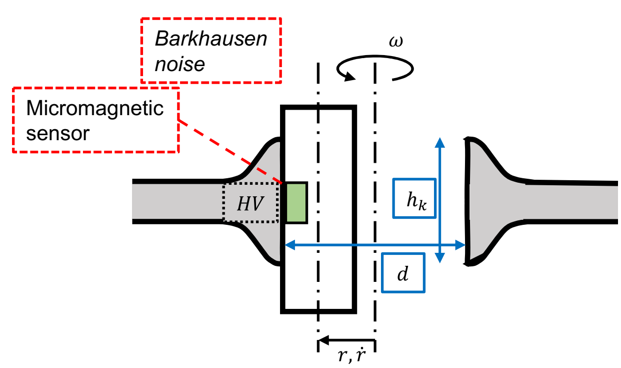

Fig. 5 Punch-hole rolling process and according softsensor concept, adapted by [14]

transformations. For this reason, a closed-loop property control is proposed in [15] to control both geometry and the α'-martensite volume fraction of AISI 304L-workpieces online during the process. The machine support contains an additional sensor system to receive the essential feedback signals to adjust the actuator trajectory (feed/axial velocity v and infeed Δr). The resulting wall thickness reduction after forming is directly measured by two laser distance sensors (Fig. 6). For the α'-martensite determination a micromagnetic 3MA-II sensor and a softsensor approach are used since α'-martensite cannot be measured online with non-destructive testing methods. The Barkhausen noise signal of the 3MA-II correlates to the ferromagnetic α'-martensite volume fraction. Additionally, the Barkhausen noise signal is also influenced by the surface of the workpiece. This surface roughness correlates to the feed in the process. The softsensor model thus contains an empiric characteristic field depending on the measurement value "maximum amplitude of Barkhausen noise (MBN)" and the process-depending parameter feed.

3.1.6 Flow forming with strain hardening control

During the incremental production of rotational hollow components through flow forming, the strength of the material changes due to strain hardening. Since there is no way to directly measure work hardening during the process, a softsensor (Fig. 7) is required. The softsensor determines the plastic strain in the component during forming, and by knowing the flow curve, the actual work hardening in the component can be calculated. In [17], a softsensor is developed using the correlation between mechanical and magnetic properties. The mean relative magnetic permeability μ_r is measured with an eddy current sensor, and the magnetic anisotropy μ_a is determined with several magnetic field sensors. The measurement is independent of the measurement

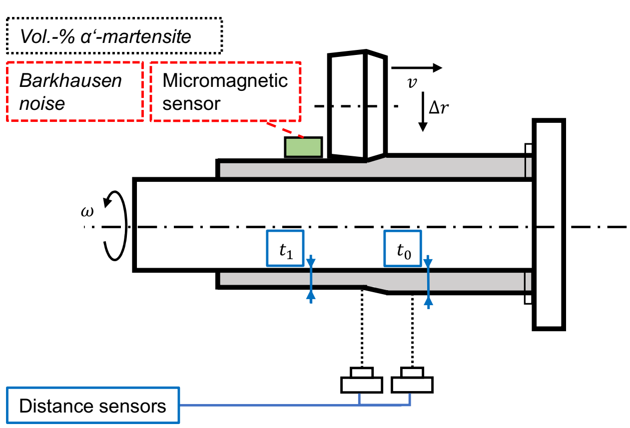

Fig. 6 Softsensor concept for a property-controlled flow forming process, adapted by [16]

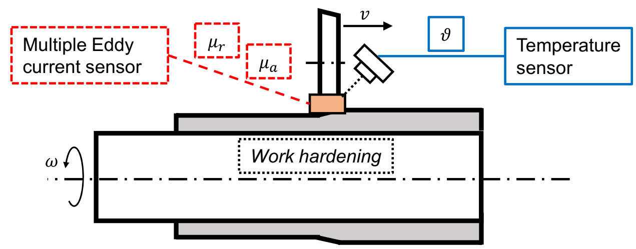

Fig. 7 Softsensor concept for work hardening measurement in a flow forming process

gap for small distances and in [18] is shown that the measurement is independent of the tilt angle between sensor and workpiece. This allows the effect separation of plastic strain and stress state. Together with the measured temperature in the measurement area, the work hardening can be calculated and finally controlled by changing the roller feed rate.

3.1.7 Multi-stage hot sheet metal forming process

Kloeser et al. also suggest a softsensor concept that can be used in a multi-stage hot forming process for process monitoring and property control purposes [19]. The forming process consists of five subsequent stages. In the first stage, a martensitic sheet metal blank (X46Cr13) is heated by induction and conduction to reach the austenitizing temperature. This is followed by hole-flanging, a combination of deep drawing and stretch drawing, and finally a die bending process. The generated workpiece is inspected in a downstream step by a micromagnetic 3MA system and laser scanner to evaluate the geometry and microstructure (see Fig. 8). The resulting microstructure is significantly influenced by the local temperature and temperature distribution of the blanks during the multi-step process chain. Thus, Pyrometers are used to locally determine the temperature. In this context, the challenge is "to reconstruct the spatial–temporal temperature distribution" of the blank [19]. An extended Kalman

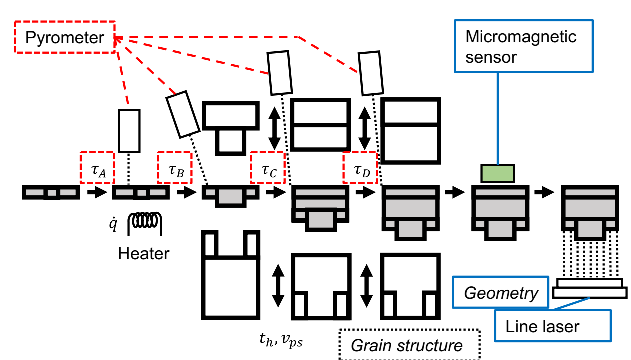

Fig. 8 Sensor concept for a closed-loop property control in multi-stage hot sheet metal forming, adapted by [19]

filter is used in the approach to overcome this challenge as the first part of the softsensor. The Kalman filter contains a reduced thermal process model that is obtained from a finite element model by proper orthogonal decomposition (POD) model reduction and an additional linearization using supporting trajectories. For the disturbance estimation a quasi-static model is assumed. The estimated temperature distribution acts as an input for the second part of the softsensor. Here, the main product properties (hardness, stresses, geometry) are deduced on the basis of the temperature and the deformation history. Kloeser et al. therefor aim to eventually utilize characteristic curves and the results from tensile tests.

3.1.8 Incremental sheet forming (ISF)

Incremental sheet forming is a highly flexible sheet forming process which is particularly suitable for prototyping and single part production of highly individual geometries. Nevertheless, the process suffers from poor geometrical accuracy. Due to the incremental characteristics of the forming process, it is very suitable for a closed-loop control of geometrical properties. Lu et al. represent in [20] a control strategy using model predictive control (MPC) to obtain improved geometric accuracy. The step depth of the toolpath is optimized based on shape feedback during the forming process (Fig. 9). In another work, this approach is extended to a two-directional toolpath correction [21]. In addition to the step depth, a horizontal toolpath correction was added to the control module in this work.

3.1.9 Progressive die bending

The springback effect in bending processes usually leads to a deviation of the final bending angle from the desired angle after unloading. Disturbance variables such as variations of the semifinished products or changing ambient temperatures hinder the prediction of this deviation accordingly. For this reason, a closed-loop controlled progressive die bending process is proposed in [22]. The forming temperature is used as a process variable to control the resulting bending angle. For this purpose, a precut specimen is heated to a defined temperature level by induction in a first forming stage. The actual progressive die bending is then applied to the specimen in a servo press in a second stage. After allocating from the press and cooling, the resulting springback angle of the unloaded workpiece is determined by two laser triangulation sensors (Fig. 10) and a geometric softsensor model that correlates the distances to springback. Finally, the springback angle is fed back through a discrete controller to manipulate the forming temperature in the next stroke.

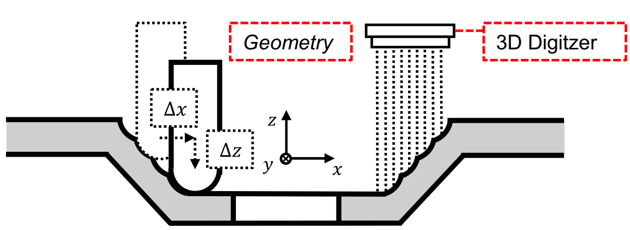

Fig. 9 Softsensor concept for single point incremental forming, adapted by [20].

3.1.10 Equipment condition monitoring: wear detection

Another category of application for softsensors is the monitoring of equipment condition in manufacturing processes. The aim in this case is to determine the tools' state, e.g. to detect tool wear. A softsensor correlates signals from different process monitoring sensors to various wear states of the tool. Thus, softsensor-based equipment condition monitoring offers new opportunities, especially for wear-prone machining technologies such as blanking.

3.2 Example for equipment condition monitoring

3.2.1 Blanking

Blanking (Fig. 11) is a highly productive process that is nevertheless under high cost pressure. Short term machine downtimes affect this negatively [23]. To prevent avoidable downtimes, it is useful to measure the wear of the tools and replace them in good time before failure occurs. In [24],

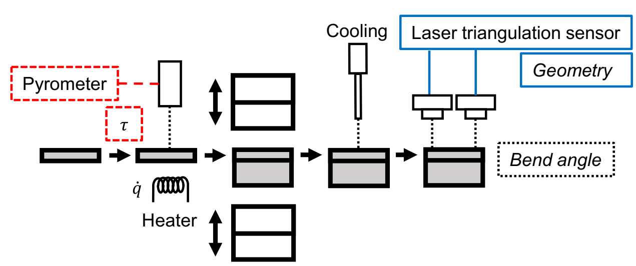

Fig. 10 Progressive die bending process with according sensor concept, adapted by [22]

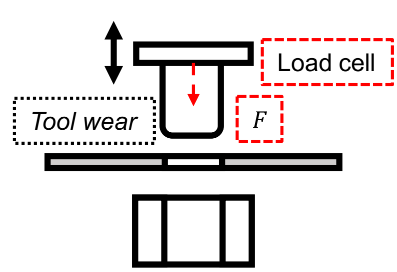

Fig. 11 Softsensor design for detecting wear in blanking, adapted by [24]

a softsensor based on force measurements is developed to determine the current wear state of the tooling in a blanking process. In this context, the authors investigated the usage of different positions of the force transducers. A comprehensive data base for preparing the softsensor model is created by recording force time series in approximately 1000 experiments with tooling in different wear states. The tool wear is quantified by measuring the edge radii. Afterwards, features are extracted from this data set by feature engineering and a principal component analysis. Eighty percent of the acquired data set is used subsequently to train a multiclass support vector machine. Twenty percent of the data is used for testing. Kubik et. al. show in their work that force correlates with punch wear and that it is possible to classify the current wear state into one of five categories. In addition, a difference in the quality of the categorization is shown for different sensor positions [24].

3.3 Redundancy

Besides softsensor applications in manufacturing processes for control and condition monitoring, softsensors could also be used in redundancy applications. Redundancy, in addition to perfection, is a method of preventing the overall failure of a mechatronic system in the event of a component failure. In safety–critical systems such as motor vehicles, aircrafts or trains, this is essential to prevent personal injury. In non-safety–critical systems, redundancy is used to prevent unexpected failures and ultimately extend the operation of the machine [25]. In recent decades due to an increasing flexibility [26] with multiple degrees of freedom in the tool [27], machine tools such as servo presses [28], have progressively developed into complex mechatronic systems. Since these machines are usually designed for an optimised service life and many years of use, total machine failure is associated with a large financial loss. In order to limit the risk of total failure despite the growing system complexity, advanced machine tools are increasingly required to have redundant structures. One way to achieve analytical sensor redundancy is to use softsensors. By using an analytical process model as an observer in combination with other sensors, measurable and non-measurable state variables of the process can be estimated. The softsensor output can then be analysed or compared to the same amount of a measured signal for fault detection and fault diagnosis. In the event of a significant, unexpected signal deviation caused by process error or a sensor failure, the system will reconfigure to another signal source, e.g. from a softsensor, thus ensuring the operation of the overall system. The following Fig. 12 shows a possible system architecture with two softsensors for redundant determination of the forming force and the ram position during punch-hole rolling with the 3D Servo Press.

In addition to the indirect measurement of the forming forces on the tool in the immediate vicinity of the forming zone, it is also possible to determine the forming forces via the torques on the eccentric drive or via force sensors on the drive rods using softsensors and the corresponding process models. Furthermore, the ram position can be calculated via the rotary encoder on the eccentric drives and a process model of the toggle joint kinematics. In this example, the redundant determination of the forming force and the ram position via different physical approaches offers various advantages. On the one hand, this can be used for error detection, e.g. a failure of the roller or the bearing, on the

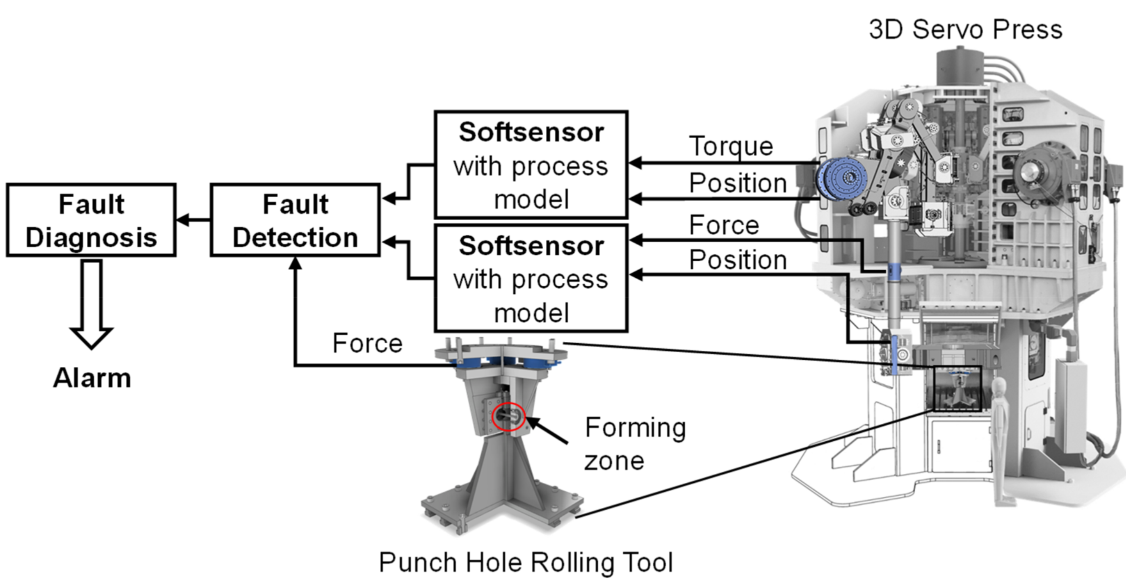

Fig. 12 Redundancy structure for determining the forming force for punch hole rolling

other hand for the detection of a faulty sensor as well as the minimisation of the modelling influences on the overall system through the multilateral approach. The challenges of building a process model increase as the position of the physical sensors is further away from the forming zone.

3.4 Positioning of the physical sensors

As shown in Chapter 2, a softsensor always consists of a physical part, which determines easily measured quantities, and a virtual part, which transforms the measured quantities into one that cannot be measured or is not feasible to measure otherwise. It is also possible that alternative measurement processes exist, but are not practical for the application at hand. The physical part consists of one or more physical sensors. To evaluate the accuracy and precision of the original measurement and thus the output of the softsensor, it is useful to consider the influence of the distance between the quantity of interest and the sensor location.

For example, the process force during a blanking process on a mechanical press is the quantity of interest. The direct measurement consists in measuring the force in the forming zone between tool and workpiece. Since it might be difficult or disadvantageous to place a sensor in the forming zone, the process force can be measured indirectly with a force sensor at a position further away from the forming zone, e.g. at the holder of the workpiece or the holder of the tool [24]. Further possibilities of indirect measurements of the process force are measuring the torque on the output of the transmission, the motor current or the deflection of the press frame [24]. The latter options are typical examples of softsensors. In general, it should be noted that the more distant the physical sensor is from the location where the force in question actually acts, the less accurate and more complicated the indirect force determination becomes. This is due to further physical effects like friction, elastic deformation or moving masses acting between the force of interest and the measured quantity. These must be taken into account in order to obtain a correct measured value. This phenomenon increases with the distance of the sensor, thus increasing the model complexity for the virtual part of the softsensor.

In Fig. 13 the presented possibilities for sensor positions are shown in an abstract form to allow the usage with different forming processes and machines. In the center, the forming zone is pictured. The outer areas are used for the measuring positions further distant from this point. Additionally, the projects which are presented in this paper are added. Besides the location of the process where the measurement is taken, the timing is also an important factor. Especially if the sensor is used for a closed-loop control, a short temporal delay between forming and measurement is preferable to reduce dead times and phase shifts inside the control loop. Therefore, the bandwidth of the closed-loop control could

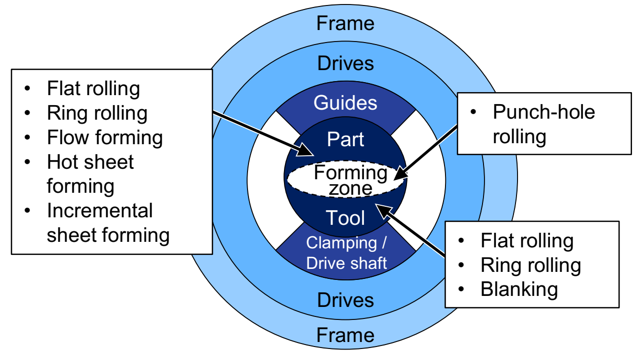

Fig. 13 Different possible positions for the physical part of softsensors, including the sensor positions in the presented projects, according to [29]

be significantly improved. At this point it should be noted that this time delay could also be caused by a spatial separation between the actuator and the sensor location in the case of moving sensors or workpieces. Apart from the temporal effect, a displacement between sensor and measurement location can also affect the measurements. A rising distance could detract the resolution of the measurement object e.g. an achievable gradation.

In general, it is preferred to measure the target values as close as possible to the forming zone in order to minimise the influence and amount of disturbances from the environment or surroundings (such as from further measurement set-ups). On the other hand, it is often not possible to measure at the preferred and near location. Additionally, the more remote measurement solutions tend to be more flexible. In this case, it must be ensured that the influence of surrounding disturbance variables (e.g. by physical shielding) is reduced or prevented, or that these influences (if known) are considered in the modelling.

In the following part, the application examples presented in Chapter 3.1 are classified by the position of the physical sensors used. The first example is the one where the rolling process is used. Here, two different physical sensors are used and combined into one softsensor. The first sensor is a thickness gauge, which determines the thickness of the incoming strip in front of the forming zone. The sensor therefore measures on the part and is time wise shifted in front of the process. The second sensor used is a force gauge which measures the rolling force. It measures on the tool but has no time shift and therefore measures simultaneously with the forming process [8]. In the example of ring rolling even more sensors are used. Overall, there are three physical sensors distributed on the tool and workpiece. The first sensor measures the tool’s position simultaneously with the forming process. The two other sensors are aligned towards the workpiece and determine its temperature on the outside and the size of the ring. Temperature measurement

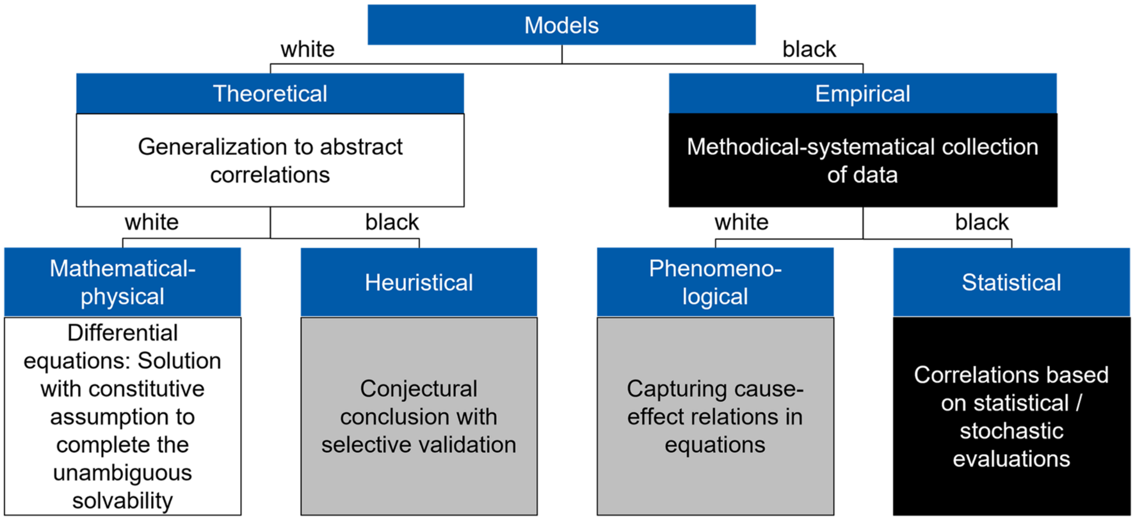

Fig. 14 Systematic of models based on their physical interpretation [30]

is performed between the forming operations, while size measurement is done simultaneously with the process [12]. In the punch-hole rolling example only one sensor is used. In this case, it is a magnetic Barkhausen noise sensor that measures the magnetic properties of the part. The special feature of this example is that the sensor is integrated into the tool, thus enabling direct measurement in the forming zone. Therefore, there is no temporal nor physical distance between process and measurement [13]. The flow forming example uses a similar measuring principle for measuring the magnetic properties. The main difference is the positioning of the sensor. In this case, the sensor is mounted close to the roller tool and points in the direction of the forming zone. There is a small axial and angular offset between sensor and forming [16]. This leads to a short delay between forming and sensing. In the multi-stage hot sheet metal forming process, multiple temperature sensors are used to determine the temperature of the part at the different stages. The sensors measure the temperature after the initial heating process and therefore have a significant temporal delay [19]. Incremental sheet forming uses a single sensor that measures the shape of the formed object. The measurement takes place simultaneously with the forming process [20]. The last presented example refers on open die bending, where two laser distance sensors are used to measure the distance to the workpiece. Therefore, the measurement is taken on the part. The measurement takes place during the forming process and thus has no temporal delay [22].

3.5 Process modelling

In recent decades, a wide variety of trends in metal forming have increased the demand for different models to meet a variety of purposes and applications in manufacturing. According to Volk et al. [30], these models can be classified on a first level as theoretical or empirical models (Fig. 14).

If the physical–mathematical relationships in the process are known and well understood, the model is referred to as a white box model on the second level. If heuristic elements are added to a theoretical model to compensate for neglected phenomena, this model is classified as a grey-box model. On the other hand, if a model is based purely on collected data, it is ranked as empirical. If no correlation or physical phenomena are known a priori and statistical relationships are formulated to develop the model, these models are called black box models. However, if the collected data are used to build a physically based model, it is also referred to as a grey box model.

The applications of soft sensors in forming processes described in the previous chapters uses different model approaches depending on the respective process knowledge. These approaches are assigned in Table 2 to the different applications of soft sensors described in this publication. In addition, references are given in which the processes as well as the underlying models are described in detail. Due to the wide range of different applications, it is difficult to make a general statement about typical model types for specific applications. However, Lu et al. [20] and Löbbe et al. [22] show that a white box model can be well used in a forming process with simplified linear physical relations. If models are needed to model friction, wear conditions [24] or processes with many influencing parameters (see [15] and [8]), black box models seem to be more suitable, especially if a large amount of data is available. Material-specific phenomenological effects can usually be well described mathematically with few data and formulated in grey box models.

Table 2 Selection of applications with different model approaches in forming technology

Model type	Process
White	Incremental sheet forming [20]
	Progressive die bending [22]
Heuristical/phenomenological	Flow forming with strain hardening [17]
	Multi-stage hot sheet metal forming [19]
	Punch-hole rolling [13]
Black	Blanking [24]
	Flat rolling [8]
	Flow forming with α'-martensite content control [15]
	(Thermomechanical) ring rolling [12]

4 Summary

This publication is based on the fact that despite the extensive application potential of softsensors in the field of forming technology, no definition of the term exists. As a basis for future work, a definition of the term softsensor in the field of forming technology and in distinction to sensor and observer is given at the beginning of this publication. To underline the extensive application potentials as well as for further explanation, extensive examples of the use of softsensors in forming processes for the strong improvement of the forming process are given afterwards. This can be accompanied, for example, by a targeted adjustment of the mechanical properties, the improvement of the geometry of workpieces or the reduction of tool wear. In addition, the aspects of redundancy, the positioning of physical sensors as well as the underlying modelling are described. Current and future investigations are aimed at further testing and improving the performance of the softsensors as well as implementing their use in other forming processes.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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