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Abstract: The high degree of individuality as well as complexity in metal-forming technology is still challenging regarding the development, integration, and operation of cognitive IoT technologies, such as sensors. In particular, the requirements for these systems in terms of robustness and sensitivity are often in conflict and prevent the widespread use of such systems. In this paper, a method for creating digital twin-based virtual sensors is introduced, which can resolve this target conflict. Furthermore, the method is linked to an approach for developing and identifying the digital twin representing the elasto-mechanical behavior of the machine under process condition to sensing technology. The resulting approach is demonstrated by creating virtual sensors to monitor the elasto-mechanical behavior of a servo-mechanical-forming press.

Keywords: digital manufacturing system; digital twin; forming; production; sensor

1. Introduction and Motivation

High requirements of machine flexibility and availability in the forming sector can be assured using monitoring solutions that ensure the orderly function and condition of forming machines [1–3]. The monitoring of process-inherent parameters during the forming manufacturing, such as the production of sheet-metal components, serve as a basis for the objectives regarding transparent, error-free production and corresponding assistance, as well as close-loop control systems [4]. Focusing on the harsh environment of forming applications (e.g., in hot metal forming) and large machine dimensions on the one hand, together with highly sensitive processes and complex forming tools on the other hand, the multiple requirements of sensor and digitization solutions occur regarding their robustness, functionality, sensitivity, or even costs [5]. Hence, the simple integration of available (partly cost-intensive) sensors for decentralized ubiquitous and direct measurements leads to high costs of these multiple sensor systems (e.g., each forming tool and machine component requires a separate sensor implementation). In addition to the high risk of sensor failure during the production operation, a high level of knowledge for operating and maintaining different types of sensors within the monitoring solutions is necessary. This leads to major obstacles in the introduction of holistic monitoring solutions in the forming sector. Moreover, a direct measurement is not feasible for each objective—e.g., for monitoring forming forces or inline machine deflection. Therefore, the development of sensor systems and analysis algorithms for indirect process and machine monitoring is indispensable for an increase in transparency, e.g., by applying smart machine components [6].

This need directly reflects the current trends, in modern production systems about digitization and increased efficiency [7]. Thus, the ability to link virtual replications of production systems and continuously update them with sensor data will form the
basis for agile and optimized manufacturing technology in the future. Hence, a virtual representation of a physically existing machine plays a key role, as these digital twins can be used throughout the entire life cycle of the production system and in different areas of the company [8]. These multiple-use cases lead to a variety of different architectures and roles of the digital twins [9]. In the context of increasing transparency and reliability in the field of forming technology, digital representation as the sum of the mechanical properties of forming machines is one of the most important types of digital twins and can then be used to extend the previous evaluation of sensor systems. Consequently, a multiplication of information content gathered by a few real sensors via a model-based approach, such as the concept of virtual sensors [10], can be achieved. In this paper, as illustrated in Figure 1, cognitive forming machines are characterized as the entirety of the physical representation of a forming machine, including real implemented sensor components and its virtual representation.

![Figure 1. Basic concept of a cognitive forming machine.](image)

Here, the virtual representation consists not only of the digital twin representing the system behavior of a forming machine, such as the elasto-mechanical structural behavior, but also involves the virtual sensor. According to [11], a virtual sensor can be defined as a software-based sensor, which combines and aggregates homogeneous or heterogeneous data signals from real or other virtual sensors. By combining and processing multiple real sensor inputs (e.g., [6,12]) through mathematical models, virtual sensors can measure conditions or process variables that cannot be monitored directly with regular measurement approaches. Here, one major benefit lies in avoiding the effort of integrating real sensors in critical machine or tool component zones with limited accessibility, which would lead to a decrease in forming system robustness. These mathematical models used for each virtual sensor can be derived by a reduction in the digital twin model. First approaches for the development and realization of cognitive forming machines are known for individual aspects of monitoring (e.g., in [12,13]). However, a method for parameter selection, development, and the identification of the digital twin for monitoring forming machines is not present. Therefore, this paper describes a concept for the development and identification of digital twin-based virtual sensors to monitor complex forming systems. The approach is demonstrated by the example of the condition monitoring of structural components of a forming press.


As already outlined, multiple sensor solutions are available for monitoring forming machines and processes, based on a wide range of physical and mechanical effects (e.g., hydraulic, thermal, and optical). One of the most essential effects of forming machines is the elasto-mechanical machine behavior, since it contributes a large share to the process stability, part quality, and machine reaction [14,15]. Hence, the elasto-mechanical behavior has a considerable impact on the entire life cycle of forming machines consisting of the phase’s
design (e.g., in [16–18]), realization (e.g., in [19–21]), usage (e.g., in [22–24]), maintenance and retrofit (e.g., in [25–29]), as presented in Figure 2.

Figure 2. Influence on and use of elastic machine behavior in the machine life cycle.

Considering the machine utilization phase, elastic machine behavior receives increasing attention in the development process of new forming tools as well as production ramp-up. In addition, the knowledge of the elastic response of forming machines and their components as well as the interaction between forming tool and machine during the forming process offer a multitude of potential methods for monitoring. Table 1 depicts a selection of essential application scenarios, which endorses the immense potential to be the base for the proposed method. In particular, the basis here is formed by indirectly measuring sensor solutions based on the virtual sensors concept [10].

Table 1. Monitoring objectives based on the elastic machine and tool behavior (exemplary selection).

<table>
<thead>
<tr>
<th>Structural Domain</th>
<th>Monitoring Objective</th>
<th>Target Variable</th>
<th>Literature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Press slide</td>
<td>PM</td>
<td>process force</td>
<td>[30]</td>
</tr>
<tr>
<td></td>
<td>PM</td>
<td>force distribution</td>
<td>[31]</td>
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<tr>
<td></td>
<td>PM</td>
<td>tilting moment</td>
<td>[32]</td>
</tr>
<tr>
<td></td>
<td>CM, PM</td>
<td>clamping forces</td>
<td>[6,13,33]</td>
</tr>
<tr>
<td></td>
<td>CM, PM</td>
<td>deflection</td>
<td>[12,13,34]</td>
</tr>
<tr>
<td>Drive train</td>
<td>CM, PM</td>
<td>forces in connecting rod acting forces (and stress)</td>
<td>[35]</td>
</tr>
<tr>
<td>Press frame</td>
<td>CM, PM</td>
<td>frame resilience</td>
<td>[36]</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>tie rod pretension, lateral post</td>
<td>[16,24]</td>
</tr>
<tr>
<td>Forming tool</td>
<td>CM, PM</td>
<td>process forces (cutting, bending, . . .)</td>
<td>[33,37–41]</td>
</tr>
<tr>
<td></td>
<td>CM, PM</td>
<td>guiding load</td>
<td></td>
</tr>
</tbody>
</table>

CM: condition monitoring; PM: process monitoring.

In stated case studies [42] virtual sensors are described, where simulation data are used as input data for virtual sensors modifying the force–path curves for a bending process. Therefore, it can be stated that the models for virtual sensors require a deep manufacturing system knowledge, such as the interdependencies between the forming process and machine. A digital twin representing these elasto-mechanic interdependencies (press behavior) offers great potential to serve as a basis for the virtual sensor data evaluation. Furthermore, the high degree of individualization and complexity of forming technologies emphasizes the need and use of digital twins for the development of robust and accurate monitoring techniques, including sensor selection and positioning, as well as the robust classification and diagnosis (algorithm for data evaluation) of the obtained data.


In this section, the method for creating virtual sensors to monitor complex forming systems, such as a metal-forming press, is proposed. Within the framework of this new approach, the digital twin is defined as the sum of the elasto-mechanical structural behavior of a forming machine, which is linked to the sensing technology. As illustrated in Figure 3,
the proposed method starts with the digital twin of a specified forming machine (step 1), which represents in detail the elastic machine behavior (stress and strain) of key machine components, such as slide, table, frame, or crown.

Figure 3. Methodical approach to create virtual sensors for complex forming systems based on the digital twin.

The identification of this digital twin can be conducted with the help of simulation models based on FE models, certain experimental analysis (as shown by the examples of the press slide and table in [43]), or by a combination of both. Using this digital twin, the virtual sensor model can be developed as characterized by steps 2 to 4. Initially, the favorable sensors, their number and positions can be derived from the developed digital twin (step 2). Similarly, the model parameters for the virtual sensors are determined based on the developed digital twin (step 3). Later on, the identified model is implemented. Finally, the verification of the developed virtual sensor model can be conducted by comparing the virtual sensor outputs with outputs acquired from temporary implemented real sensors (step 4). In the remainder of this article, the core elements of the proposed method are explained in detail by creating virtual sensors to monitor the elasto-mechanical behavior of a forming press due to the changes in the acting forces during the forming operation.

4. Validation of the Method on a Complex, Real-Typical Mechanic Press

4.1. Digital Twin Representing System Behavior

The knowledge about the acting interdependencies in the system is essential to ensure not only a sufficiently accurate digital twin, but also a secure, robust and sufficiently accurate measurement. Thereby, the system environment consisting of the forming tool and their interacting machine components, the implemented process technologies, such as the deep drawing process need to be considered in the simulative analysis. To demonstrate the proposed method, the focus was set on the development of virtual sensors to monitor the mechanical stress and strain behavior of the structural components of a 1 MN servo-eccentric press due to changes in the acting forces during the forming operation, as illustrated in Figure 4a. Initially, the digital twin was built using an FE model describing the elastic machine behavior of this press, as shown in Figure 4b,c.
To cover a wide spectrum of forming technologies and forming tools, varying load cases (LCs) were realized in the simulative analysis. Figure 5a depicts the simulated 25 LCs with an acting force induced through a single steel plate (500 mm × 500 mm × 100 mm) representing a small forming tool. By selecting different distances regarding the x- and y-coordinates, respectively, forming tools with centric and eccentric force applications can be represented in a simplified way in simulative and experimental analyses. Each LC consisted of varying force magnitudes between 100 and 1000 kN in 100 kN steps. Thus, a system of basic load cases was established covering the whole working space of the press via linear combinations. Regarding the boundary conditions of the FE model, a fixed support was defined at the machine’s foundation. To keep the calculation effort of the FE analysis appropriate, the mesh size was demand driven. Only in the regions of interest like the press columns, the clamping surfaces of press slide, as well as the table and contact areas between the components, a finer mesh was used for a more accurate computation of stress and strain states.

To verify the developed FE model, which is the base of the desired digital twin, experimental measurements were conducted using an existing approach [43]. By implementing strain sensors at the defined positions (such as in Figure 5b), it was possible to compare the simulated and real strain values for each LC and force magnitude. For a centric LC with a force magnitude of 600 kN, the simulated elastic strain reached values of about 29 μm/m, which was confirmed by the measurements, as outlined in Figure 5c.
4.2. Sensor Selection and Positioning for Virtual Sensors

Hence, the simulated elastic stress and strain changes for the components, press crown, columns, press slide, and machine foundation present highly sensitive and even critical zones marked with red circles in Figure 6, which are depicted by high stress values.

![Figure 6. Simulative analysis for example assemblies regarding sensor selection and positioning.](image)

Based on these simulation results, classic strain gauges are a promising sensor approach to detect this elastic machine behavior. Referring to this digital twin in the form of these simulation results, a knowledge-based evaluation of the number of sensors and their positioning was conducted, as illustrated in Figure 6. Here, not only can the critical zones be the sole criterion, but also the accessibility as well as significant feedback effects of the sensor integration on the measurement process and press structure was considered in the sensor selection and positioning process. On this basis, the selected real sensors were highlighted with red marks, while the virtual sensors were highlighted with blue marks. Real sensors were integrated in zones with high strain changes and good accessibility to serve as inputs for the virtual sensors that were positioned in critical zones with limited accessibility.

4.3. Model Reduction in Digital Twin to Identify and Implement the Virtual Sensor Model

The fundamental model for one virtual sensor can be derived by a model reduction of the digital twin developed and verified in Section 4.1. In essence, the virtual sensor model is defined as the relationship between the input variables in the form of strain or mechanical stress values of real sensors and the target variables in the form of virtual sensor data. This relationship can be described using transfer functions or matrices.

These transfer matrices, for instance, represent the virtual sensors as a weighted linear combination of polynomials of the real sensors. Using the digital twin to identify the parameters of the virtual sensor model, a load case-based approach was proposed, where a base of several characteristic LCs was defined assuming that every real LC can be equated with a linear (or even nonlinear) superposition of weighted LCs derived from the load case base. Typical LC or single loads are gravitational force, centric-induced press force, tilting moments resulting from an eccentric press force application, and pretension resulting from tie rods. Due to the base LC $k$ with their nominal loads $T^k$ and the previously determined and at the base load cases compartmentalized real typical loads $T^k$, the strain and von Mises stress values of a single virtual sensor $v_i$ can be calculated as the summation of weighted functions $f^k$ and the system-dependent factor $a_i^k$

$$v_i = \sum_{(k)} f^k / T^k, a_i^k$$  (1)
A comparison between the output of a virtual sensor and the output of the FE model experimentally verified in Section 4.1 determines the accuracy of the performed model reduction. Figure 7 shows this comparison for stress values for every LC.

![Figure 7. Comparison of virtual sensor output to output of FE model.](image)

Here, the relative error resulting from this comparison reached values of 2.7%, which supports the assumption that highly accurate outputs can be obtained using virtual sensor models specified as simplified digital-twin models.

### 4.4. Model Verification of Virtual Sensor Function

In the final step, the verification of the developed virtual sensor model can be conducted on two levels. Figure 8a shows an exemplarily verification sensor, which was temporarily installed at the position of a virtual sensor located at the press crown.

![Figure 8. Verification of the developed virtual sensor model.](image)

Based on the experimental analysis mentioned in Section 4.1, the direct comparison of the output of a virtual sensor and the corresponding real verification sensor for a centric LC with a force magnitude of 600 kN shows on a qualitative and quantitative level comparable values, as seen in Figure 8b.

### 5. Summary and Outlook

The elasto-mechanical behavior of forming machines and their forming tools is the decisive indicator, which allows a general assessment of the machine and process condition over the entire life cycle. By combining digital twins representing the elasto-mechanical press behavior and local real sensor data, cognitive forming machines can be realized. In this article, a novel method for creating digital twin-based virtual sensors to monitor complex forming systems, such as a sheet-metal-forming press, was introduced. Furthermore, the method is linked to an approach for the development and identification of a digital twin.
representing the interdependencies between machine and process to sensing technology. Consequently, the manufacturing system knowledge embedded in the digital twin is not only linked to sensor selection and positioning, but also to the development of the underlying virtual sensor model as well as data evaluation. For the verification, the proposed method was successfully demonstrated by creating virtual sensors to monitor the elasto-mechanical behavior of a servo-eccentric-forming press. It can be stated that the proposed method creates the prerequisite for an increase in process transparency. Figure 9 illustrates the potential benefit offered by linking digital twins with virtual sensors reflecting the entire life cycle of forming machines.

Figure 9. Potential benefits offered by digital twin-based virtual sensors.

In addition to the possibility of increased process and condition monitoring (e.g., asymmetrical load distribution on forming machine), the offered information can serve as input data to enable more accurate simulations for process design in the future and a more load-oriented design of forming tools, reducing the try-out time and cost for forming tool transfers to alternative presses and thereby promises a growth in productivity.

In future studies, the effort to develop and identify digital twins needs to be reduced, especially for existing forming presses without design documentation as well as the model verification process. Moreover, the developed method should be applied using the described sensor systems in [6,12,13,31,32,34,40] as a basis to identify process-inherent parameters, such as the deflection and process force distribution during the forming operation. The challenge here is to ensure a secure correlation path between these sensing elements and the application environment and would enable the identification of previously unknown in-depth interdependencies regarding elasto-mechanical machine behavior (e.g., process force distribution at the tool clamping interface). Increasingly, the proposed method shows great potential to be a key part of the development process of digital usage-based business models [44].

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