Monitoring & Control

Research Group TEC | Manufacturing Technology

White Paper

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1. The Cluster Monitoring & Control within the TEC research group

1.1. What is Monitoring & Control in Production Engineering?

The fundamental target figures in production of goods are quality, economic efficiency, velocity and variability. Particularly in complex, global production networks, the importance of the latter increases, as there are a large number of different factors influencing processes, process chains and supply chains, which can decide on manufacturability or deliverability. In this context, responsiveness and adaptability are essential. In the course of digitalization in the production environment, new opportunities and possibilities arise for process and component monitoring and how to make processes transparent, with regard to the target figures. The extensive amount of available data about conditions, process or quality indicators in combined with innovative models (see Cluster Advanced Modeling) allow the discovery of new complex relations and the approximation to an optimum between several target figures. Therefore, for example process and thus quality deviations can be detected or predicted at an early stage, or component or rather tool wear can be monitored. In the next step, real-time monitoring allows active intervention in the process or rather process control as a reaction to events, deviations or irregularities in order to continue achieving the corresponding target figures.

In the course of increasing product individualization and increasingly dynamic global markets, the target parameters of flexibility and adaptability will be increasingly interesting, which means that responsiveness and adaptability will play a decisive role. Especially with regard to short-term responsiveness, the approaches of innovative solutions in the afield of Monitoring & Control provide a decisive contribution. In addition, however, there is also the requirement to provide adaptable Monitoring & Control solutions in order to be able to be applicable in a wide variety of applications and systems and thus to achieve scalability for the range of data-driven production.

Another important context is the increasing environmental awareness and thus the striving for a sustainable and efficient use of resources in society. This results in new parameters and targets with regard to the analysis and evaluation of aspects of sustainability and resource efficiency in production. Monitoring & Control aims to gain knowledge of the interdependencies between the new parameters and targets in order to initially create transparency and thus ensure compliance with limit values or to be able to optimize processes with regard to the new targets.

1.2. Research group TEC

Since the beginning of 2021, we have jointly formed the research group TEC | Manufacturing Technology within the Institute for Production Management, Technology and Machine Tools (PTW) at Darmstadt University of Technology. Our vision is to conduct trend-setting research for data-driven, adaptable manufacturing technologies in resource-efficient, responsive production. Enthusiasm for our research, a high level of commitment and initiative, as well as openness and curiosity in breaking new ground are essential characteristics of our TEC team.

The TEC research group has grown together from the three former research groups *Additive Manufacturing*, *Machine Tools and Industrial Robots*, and *Machining Technology*. Thus, we are able to cover a broad field of manufacturing technology. Shortly after the changeover, the closer cooperation in the TEC research group became apparent through simpler communication, as well as more agile project application and processing. In order to address specific topics, the research clusters *Smart Components*, *Advanced Modeling*, *Connectivity & Communication* and *Monitoring & Control* were established in the TEC research group. However, these clusters do not represent strictly delimited groups, but are rather to be understood as open spaces for exchange among the colleagues. This enables a differentiated view of the topics from different directions and ensures a targeted exchange of experience and knowledge.

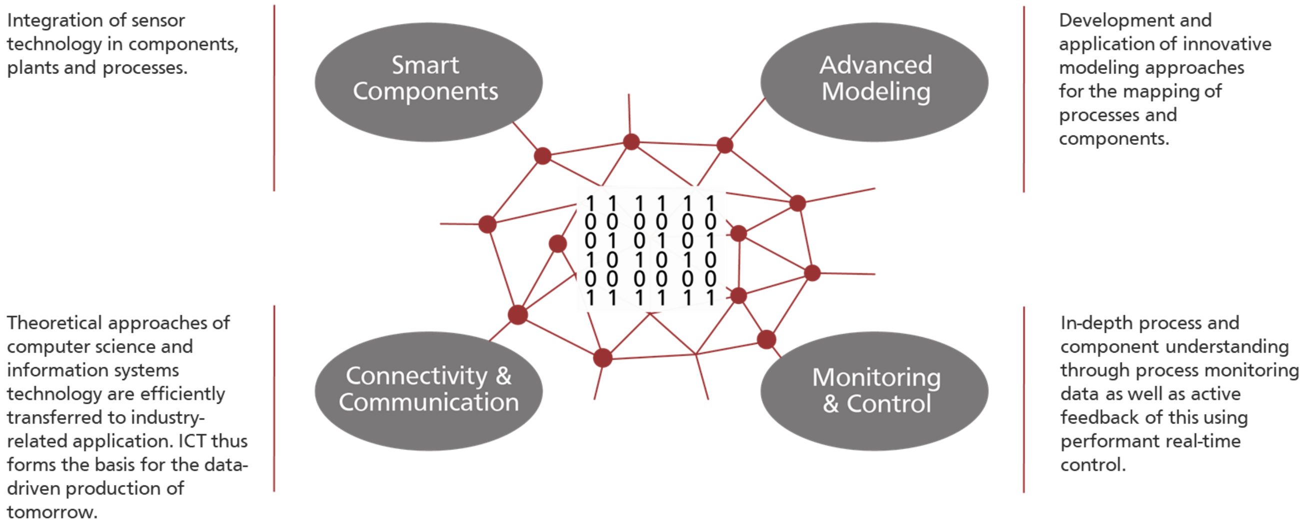


Figure 1: Expertise of the clusters within the TEC research group

With the TEC-Lab, PTW has a technical center with a climate-stable measurement and sample preparation room as well as modern machinery. It provides the perfect environment to quickly develop and test new approaches for data-driven manufacturing using agile methods in a solution-oriented manner. With various demonstrators for data-driven manufacturing technologies and networked production solutions, the fun and enthusiasm for data-driven production is also awakened among young scientists.

Figure 2: TEC-Lab at PTW

2. Monitoring & Control in future machining

2.1. Vision

Based on connected production and novel smart components, the variety of available data enables conclusions to be drawn about system or process states. This data is an additional resource in the production of the future, whose potential can be uncovered through interpretation and evaluation. This value creation from data to information as well as the feedback into the process is the goal of the Monitoring & Control cluster.

Various approaches are available for this purpose, for example empirical models or machine learning approaches. In this way, usable and value-added information can be generated from simple data. Examples of applications are quality assessment by means of anomaly detection in sensor signals, tool wear assessment via process forces and life cycle assessment based on the individually used resources.
Based on these, a control or regulation-based adaptation of processes can take place (see Cluster Advanced Modeling) with the goals of maximizing productivity, minimizing wear, increasing quality or increasing energy efficiency for a flexible and adaptable production of the future. In addition, new types of digital services and payment models as well as socio-economic developments will be made possible, which will decisively shape the value chains of the future.

2.1.1. Process monitoring as a key enabler of data-driven quality assessment

Process Monitoring provides the data for the evaluation of processes. This data can be upgraded to process information by post-process evaluation and used, for example, to make quality statements at the end of the production chain. It can also be used during in-process processing in real-time approaches to monitor process parameters and sensor data to detect process anomalies.

Compared to post-process methods, the monitoring of process parameters and process states in parallel to the process offers enormous potential for increasing resource efficiency and sustainability, since deviations from target states are not only detected at the end of the process or the process chain and can thus still be corrected in the process itself (process control). Above all, the data generated in the course of controlling machines and systems is still insufficiently used today as a resource for gaining deeper insights into manufacturing processes.

In the area of process monitoring, research is being conducted into how the variables describing the process can be determined in parallel with the process and made available for evaluation in sufficient quality. The focus here is on how process parameters can be determined from data that is already available but mostly unused today. Advanced Modeling approaches and additional new sensor technology from the field of Smart Components can be used to generate additional information that was previously inaccessible for evaluation. As a result, new and more comprehensive evaluation possibilities of the processes arise and thus the possibility of developing a digital fingerprint of the respective process. The evaluation of the quality of the acquired data in the environment of new data infrastructures such as GAIA-X are also part of the research in the area of process monitoring.

2.1.2. Condition Monitoring

Condition monitoring describes the automated monitoring of machine components by means of sensor data. The aim is to achieve high correlation between the measured physical variables and the state variables in order to conclude on necessary interventions. A very well-known application is, for example, the diagnosis of the tool wear condition during machining. However, since the raw sensor data usually do not allow direct diagnosis, system models are often used here as well.

Condition monitoring is the prerequisite for condition-based or predictive maintenance, in which the remaining useful life is predicted. This can replace conventional reactive and preventive maintenance strategies. The benefits lie primarily in machine and resource efficiency. In current research projects, we are developing innovative approaches for applying predictive maintenance on machine components, such as on rolling bearings, ball screws or bellows, which will lead to disruptive changes in machine maintenance in the future.
The technologies for data-driven condition monitoring will also bring new innovative business models to the market. The determination of machine stress factors enables the introduction of stress-oriented

payment models (*pay-per-stress*), which are particularly beneficial in a volatile market with fluctuating orders.

2.1.3. Process Control

Process control desribes the preservation of a previously defined or optimized process condition through continuous monitoring and appropriate corrections. Process control is thus based on process and condition monitoring. The aim is to ensure consistent process quality under the influence of uncertainties and disturbances. The process quality can be defined on different levels, e.g. as resulting component quality or also under aspects of energy efficiency and sustainability (e.g. tool wear). The control of the process can be based on predictive models (e.g. quality prediction based on live process data) as well as on real-time capable control methods. The stored models and control methods are used to adapt the process accordingly and thus react to deviations in the process state. In addition, self-learning control concepts can be implemented, increasing reliability and flexibility.

In the data-driven adaptive production of the future, process control represents a central aspect of responsiveness. This means that both small batches can be manufactured efficiently and the process can be operated on a rule-based basis using the target variables of the process state. Furthermore, control-based manufacturing has the ability to respond to local and global changes in networked production. In this way, uncertainties in production can be compensated for and aspects of sustainability can be integrated into production. If, for example, an upstream or downstream system fails at short notice, the current production process can be adapted and switch from maximum productivity to low-wear and sustainable production parameters while maintaining the required component quality.

2.2. Use Cases

			Use-Case
Quality Management	Product	Process Monitoring	**Annomaly detection** in additive manufacturing: Laser-based powder bed melting enables the evaluation of the component quality for the entire component volume due to the layer-by-layer structure. With the aid of optical monitoring systems, both a comparison to a reference process and a component-specific process evaluation via process anomalies can take place. The correlation between the characteristics of the process anomaly and the resulting defect enables the evaluation of the component quality. Sensor data fusion can be used to detect different defect types and improve the prediction accuracy of the defects.
			For the detection of **process uncertainties** in tapping, a sensor-integrated tap chuck was developed, which is equipped with two new sensor concepts that allow the detection of the immediate vibrations of the tapping tool[1] as well as the axial length compensation[2]. The measurement data, recorded at up to 52kHz, is stored directly on the telemetry unit, allowing reliable analysis of the measurement data downstream to identify signal features for process uncertainty detection. This system architecture enables the detection of process uncertainties in the tapping process.
			Process-parallel **quality determination** during milling: Based on machine data (actuator current, position data) and external sensors (force measurement platform, vibration data on the tool), the resulting component quality is estimated. This enables downstream quality steps to focus on components with significant process anomalies.
	Machine / Tool	Condition Monitoring	**Tool wear** is a central source of defects for poor component quality. Therefore, tools are often replaced preventively. This makes neither economic nor ecological sense. To counteract this practice, a camera-based wear detection system was developed. This checks the tool wear in the machine tool at defined intervals and can predict the remaining service life from learned ML-based models.
			Tool pullout: A frequent quality problem in the machining of high-strength alloys (Ti64, In718, FeAl) is shape deviation due to tool pull-out. Detecting this at an early stage and either stopping the process and changing the tool or applying a compensation strategy depending on the pull-out length can be realized on the basis of process monitoring with supplementary process control. This reduces scrap, especially in the case of complex aerospace components.

			Use-Case
Process Optimization	Machine	Autonomous Machining	**Individual part production:** The demand for flexible and customized production of components calls for an efficient "first-time-right" approach. The adaptation of the manufacturing process can be realized via the specific mapping of geometric features and correspondingly suitable process parameters. Component quality is ensured without a reference process on the basis of known correlations between similar geometric features and process parameters and the correlating resulting properties.
			Tool displacement: Machining by means of industrial robots is an approach to economically process large component volumes in particular. Stiffness-induced challenges in mapping accuracy are answered by compensation strategies in path planning. These can be implemented both as predictive process control and in the form of process control based on the data recorded parallel to the process.
		Energy	Based on internal machine data (actuator currents, process times, forces) of past processes as well as the process parameters and geometry information of a planned production process, the required **energy** can be estimated predictively.
			In addition to process quality**, energy consumption** and thus the **ecological footprint** will in future be achieved through energy-adapted processes.

[1] T. Öztürk, M. Weigold, „Sensorvorrichtung zum Erfassen werkzeugnaher Schwingungen beim Bearbeiten eines Werkstücks mit einem Werkzeug“, patent pending, application number: DE 10 2021 100 465.9

[2] T. Öztürk, M. Weigold, „Sensorelement und Sensorvorrichtung zum Erfassen eines axialen Längenausgleichs in einem Längenausgleichsfutter beim Bearbeiten eines Werkstücks mit einem Werkzeug“, patent pending, application number: DE 10 2021 100 466.7

3. Projects and offers to the industry

3.1.1. SensoSchu

The Sensory Protective Cover project is classified in the Condition Monitoring area within the Monitoring & Control cluster. Flexible protective covers are used to protect moving machine components from contamination and to safeguard danger zones. If signs of wear on the protective cover are not detected in time, this can lead to considerable damage to the machine and long downtimes. In the project, protective covers were enhanced with sensors and machine learning methods were used to enable self-diagnosis of the condition. Predictive maintenance including timely replacement to maintain the protective function is thus made possible.

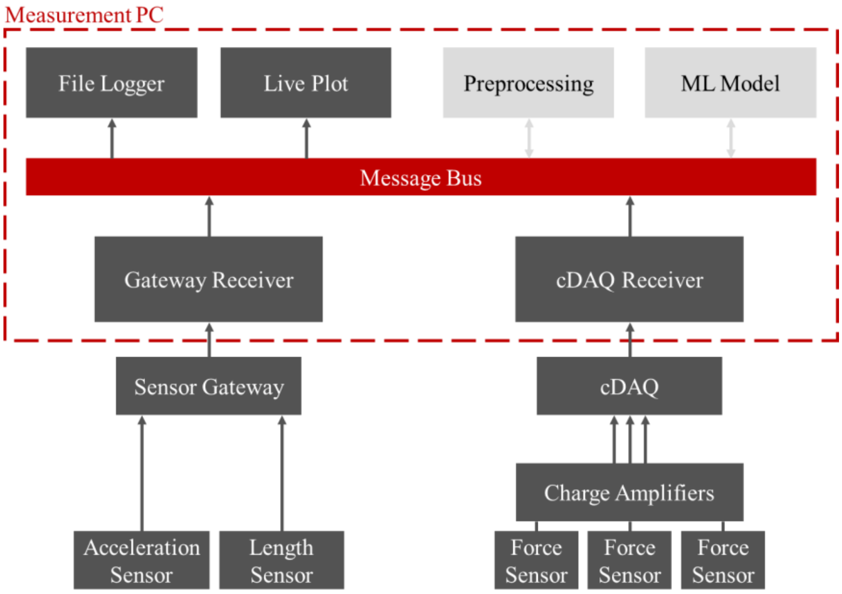


Figure 3: Exemplary system architecture of a smart component for monitoring application[3]

3.1.2. TensorMill

The "TensorMill" project focuses on the development of a networked, intelligent process chain for milling production of integral components. The aim is to use artificial intelligence to increase the robustness of manufacturing processes. To react to as many situations as possible in the process chain available data acquired during the manufacturing processes will serve as the basis. The basis for this is provided by holistically networked production, from tool manufacture and machining to end-of-line quality measurement. The merged data streams enable collected information and process-relevant data to be made available to users along the value chain through a technology app. This forms a cloud-based digital twin. Machine-side and workpiece-side monitoring units are developed to determine process-relevant data in the context of autonomous milling. The main task of the machine-side monitoring unit developed at PTW is the process-parallel recording and contextualization of machine tool data, which provide the basis for AI-based decision-making. For this purpose, suitable models and algorithms for determining the tool condition and the quality of the manufactured workpiece are trained and evaluated. This project thus provides the basis for the PTW use cases for data-based, process-parallel tool condition determination and quality prediction.

[3] F. Hoffmann, B. Brockhaus, J. Metternich, and M. Weigold, "Predictive Maintenance für Schutzabdeckungen/Predictive maintenance for protective covers – From business model to application," wt, vol. 110, 07-08, pp. 496–500, 2020

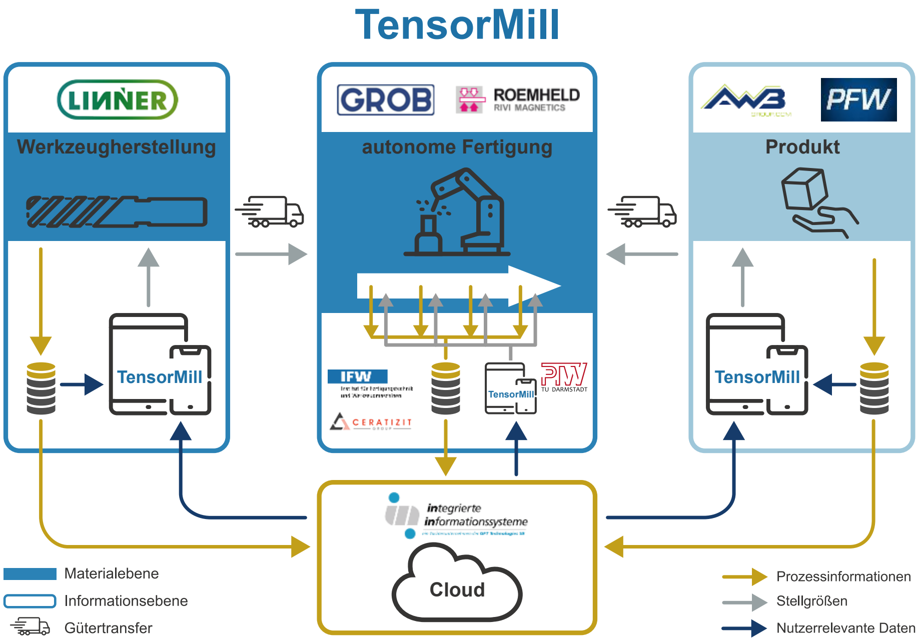


Figure 4: Concept for increasing productivity based on intelligent, networked autonomous manufacturing for the production of safety-relevant integral components for the aerospace industry

3.1.3. AICoM

The aim of the project "AICoM - Artificial Intelligence Controlled Milling" is the development of "AICoM" in the form of an intelligent modular system and control architecture for modern machine tools. The system AICoM enables the optimization of the CAD/CAM production chain up to the manufacturing of the products. The combination of AICoM with a modern machine tool creates the "learning machine tool" for metal cutting production with the ability to autonomously adapt the process and rely on learned "knowledge" or learned "experience". This is done by integrating novel artificial intelligence methods into the developed system and control architecture. For this purpose, new approaches based on automated machine learning (AutoML) are developed, which enable domain experts to create AI models in reduced time. The core of the lies in the AI-based process control, whereby the machine tool autonomously adapts to user-selected target variables. In addition to the process parameters, AICoM also adjusts the previously calculated path points in order to react to any machine condition based changes or disturbances. As a result of the project, technologies are being developed that automatically plan the process strategy and parameters and autonomously carry out the processes for metal-cutting production.

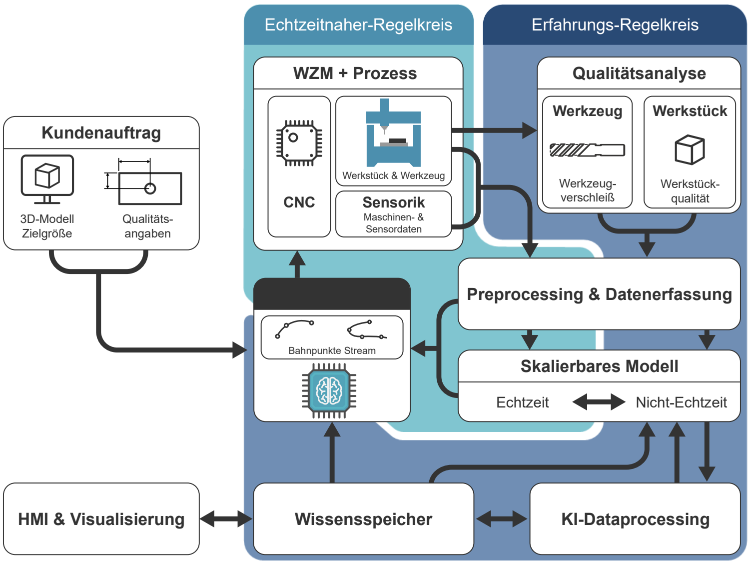
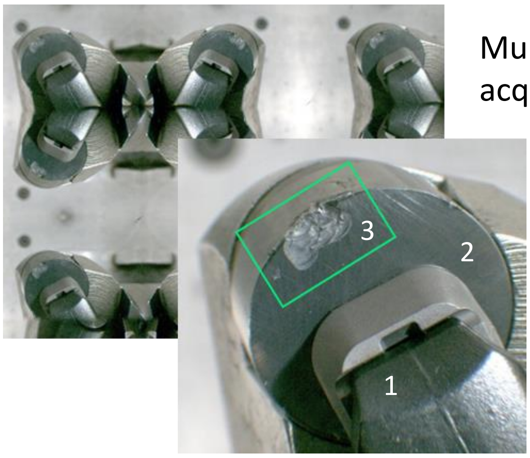


Figure 5: Presentation of the concept of the intelligent modular system and control architecture "AICoM" for the learning machine tool

3.1.4. AVISPA II

The project Automation of Visual Inspection and Finishing processes for Aero-engines is situated in the field of Condition Monitoring and Quality Inspection within the Cluster Monitoring & Control. The competitiveness of the European aero-engine industry can be significantly improved by a zero-defect approach for selected components and manufacturing processes. This will be achieved by implementing automated image-based inspection processes, machine learning (AI), process automation and control loops in critical manufacturing processes. Key areas of interest include predictive monitoring of cutting tool wear in machining processes, closed-loop control of various machining techniques, such as abrasive surface machining of additively manufactured engine parts, and automation of visual inspection of components with honeycomb structures to detect complex assembly issues and defects.



Multiview-Lightfield-Image of the cutting tool acquired via an image-multiplier

Extraction of the worn area on the cutting edge used for the classification of the state of tool-wear

1 - Tool holder

2 - Cutting insert

3 - Worn area

Figure 6: Image-based classification of the state of tool wear for industrial cutting inserts

3.1.5. Pay-Per-Stress

The aim in the Pay-per-Stress project is to develop and prototype a load-oriented payment model for use with machine tools. The dependence of the leasing rate on the load of the machine has the potential to make the leasing of complex machines more efficient and fairer. For this purpose, knowledge of the actual stress on the machine as well as its components is taken into account on the one hand, and an understanding of the cause-effect relationship between machine stress and wear on the other. The stress factor developed from this serves as a monetary evaluation unit for the pay-per-stress approach and as a basis for the further development of existing business models towards intelligent service offers. In addition to evaluating the required data on the basis of artificial intelligence, blockchain technology is used for legally compliant data exchange.

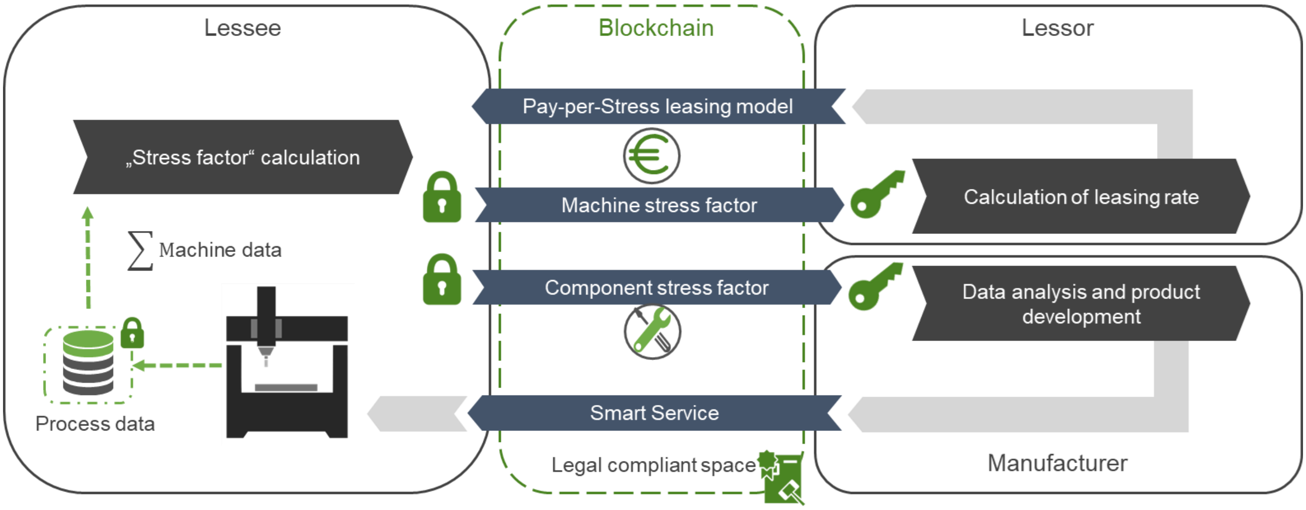


Figure 7: Concept for the implementation of Pay-per-Stress

3.1.6. AddLight

In the project AddLight, innovative manufacturing and dimensioning concepts for lightweight structures are being developed based on physics-based models (white box) in combination with data-based machine learning methods (black box). This enables reproducible, automated generation of arbitrarily complex geometries and thus industrial series-production capability of lightweight structures in dynamically loaded components manufactured using additive manufacturing. Laser-based Powder Bed Fusion (LPBF) is used. By means of process monitoring systems, the component properties resulting from the process can be predicted. Based on this study, predictive process control is developed to homogenize the process. The result is a manufacturing process with a significantly lower number of process anomalies, resulting in a more homogeneous microstructure and a lower number of defects. The remaining process anomalies should be reliably detected by the process monitoring systems. The aim is to realize in-situ quality assurance.

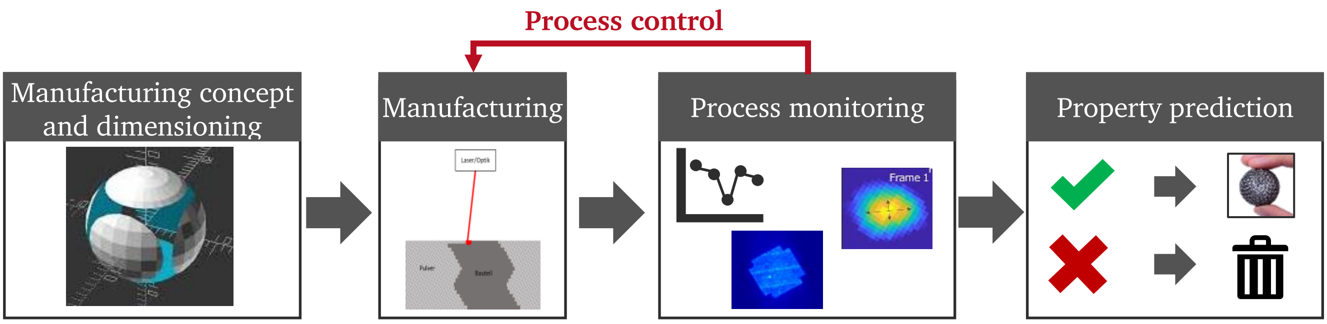


Figure 8: Illustration of the interaction of the AddLight topics with each other

4. Dissemination of knowledge

In addition to courses for students and industry partners, we implement the knowledge gained in demonstrators that serve to reinforce knowledge and provide training and further education. In the Monitoring & Control cluster, there are several demonstrators that are intended to address the target group of industry on the one hand and students of mechanical engineering, computer science and mechatronics on the other. The demonstrators are intended to demonstrate the possibilities of monitoring and control and to be experienced in minimal examples in the TEC-Lab. On the other hand, in interaction with processes on the machines in the TEC-Lab, they are intended to show the direct benefits in manufacturing for process description and, in connection with the research cluster Advanced Modeling, the potentials of data-driven models for process description. The basis for the demonstrators and their continuous further development are the considered use cases of the research projects.

5. List of Publications

- A. Ziegenbein, A. Fertig, J. Metternich, and M. Weigold, "Data-based process analysis in machining production: Case study for quality determination in a drilling process," Procedia CIRP, vol. 93, no. 4, pp. 1472–1477, 2020, doi: 10.1016/j.procir.2020.03.063.
- P. Stanula, C. Praetzas, O. Kohn, J. Metternich, M. Weigold, and A. Buchwald, ""Stress-oriented, data-based payment model for machine tools"," Procedia CIRP, vol. 93, pp. 1526–1531, 2020, doi: 10.1016/j.procir.2020.03.080.
- E. Sarikaya et al., "Data Driven Production – Application Fields, Solutions and Benefits," 2021. doi: 10.26083/tuprints-00017874
- H. Merschroth, J. Harbig, and M. Weigold, "Defect detection based on sensor data fusion of optical monitoring systems in laser based Powder Bed Fusion," in Laser Congress 2020 (ASSL, LAC), Washington, D.C, LTh1B.3. doi: https://doi.org/10.1364/LAC.2020.LTh1B.3
- O. Kohn, A. Fertig, B. Brockhaus, and M. Weigold, "In Maschinendaten Fehler beim Gewinden detektieren/Detection of process errors during tapping in machine tool data," wt, vol. 111, 01-02, pp. 20–24, 2021, doi: 10.37544/1436-4980-2021-01-02-24.
- O. Kohn, P. Stanula, E. Lang, M. Weigold, and J. Metternich, "Development of a Stress Factor as an Indicator for Stress-Based Payment Models for Machine Tools," in Lecture Notes in Production Engineering, Production at the Leading Edge of Technology, B.-A. Behrens, A. Brosius, W.-G. Drossel, W. Hintze, S. Ihlenfeldt, and P. Nyhuis, Eds., Cham: Springer International Publishing, 2022, pp. 239–247. Doi: https://doi.org/10.1007/978-3-030-78424-9_27
- H. Merschroth, M. Kniepkamp, and M. Weigold, "Predicting and Controlling the Thermal Part History in Powder Bed Fusion Using Neutral Networks," in Proceedings of the 30th Annual International Solid Freeform Fabrication Symposium, 2019, pp. 161–171. [Online]. Available: http://tubiblio.ulb.tu-darmstadt.de/119442/
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- A. Fertig, O. Kohn, B. Brockhaus, and M. Weigold, "Consistent Contextualisation of Process and Quality Information for Machining Processes," in Lecture Notes in Production Engineering, Production at the Leading Edge of Technology, B.-A. Behrens, A. Brosius, W.-G. Drossel, W.

Hintze, S. Ihlenfeldt, and P. Nyhuis, Eds., Cham: Springer International Publishing, 2022, pp. 195–2022. Doi: https://doi.org/10.1007/978-3-030-78424-9

- B. Brockhaus, F. Hoffmann, J. Metternich, and M. Weigold, “Predictive Maintenance for Flexible Protective Covers in Machine Tools,” in Lecture Notes in Production Engineering, Production at the Leading Edge of Technology, B.-A. Behrens, A. Brosius, W.-G. Drossel, W. Hintze, S. Ihlenfeldt, and P. Nyhuis, Eds., Cham: Springer International Publishing, 2022, pp. 177–185. Doi: https://doi.org/10.1007/978-3-030-78424-9_20

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