AI-based Framework for Deep Learning Applications in Grinding

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***Abstract*—*Rejection costs for a finish-machined gearwheel with grinding burn can rise to the order of 10,000 euros each. A reduction in costs by reducing rejection rate by only 5-10 pieces per year already amortizes costs for data-acquisition hardware for online process monitoring. The grinding wheel wear, one of the major influencing factors responsible for the grinding burn, depends on a large number of influencing variables like cooling lubricant, feed rate, circumferential wheel speed and wheel topography. In the past, machine learning algorithms such as Support Vector Machines (SVM), Hidden Markov Models (HMM) and Artificial Neural Networks (ANN) have proven effective for the predictive analysis of process quality. In addition to predictive analysis, AI-based applications for process control may raise the resilience of machining processes. Using machine learning methods may also lead to a heavy reduction of cost amassed due to a physical inspection of each workpiece. With this contribution, information from previous works is leveraged and an AI-based framework for adaptive process control of a cylindrical grinding process is introduced. For the development of such a framework, three research objectives have been derived: First, the dynamic wheel wear needs to be modelled and measured, because of its strong impact on the resulting workpiece quality. Second, models to predict the quality features of the produced workpieces depending on process setup parameters and materials used have to be established. Here, special focus is set on deriving models that are independent of a specific wheel-workpiece-pair. The opportunity to use such a model in a variety of grinding configurations gives the production line consistent process support. Third, the resilience of analytical models regarding graceful degradation of sensors needs to be tackled, since the stability of such systems has to be guaranteed to be used in productive environments. Process resilience against human errors and sensor failures leads to a minimization of rejection costs in production. To do so, a framework is presented, where virtual sensors, upon the failure or detection of an erroneous signal from physical sensors, will be activated and provide signals to the downstream smart systems until the process is completed or the physical sensor is changed.*

Keywords*—*Cylindrical Grinding, Wheel Wear, Virtual Sensors, Process Resilience, Artificial Intelligence

I. INTRODUCTION

In 2009 the European Research area of the European Commission published a document about the strategy for a sustainable European machine tools industry (European Commission, 2009) that divides the research in the machine tools industry into five sub-projects. One of those five sub-projects, is "The Manufacturing Break-through" and it is written that "In this case four demonstrators are envisaged, illustrating self-calibration, predictive maintenance, versatile configuration, and improved control of accuracy and acceleration at high operating speeds." [1]. It is observed that 20-25% of total cost towards any machining job comes from grinding processes [2]. Metallic high-performance alloys such as titanium or high-strength steels, require effective and efficient machining due to their heavy machinability. Because of the high demands placed on the geometric shape, surface and surface area, grinding is a highly effective manufacturing process in the finishing of camshafts or gearwheels, for example. The increasing production pressure and decreasing cycle times force production employees to process the workpieces faster in less time that inevitably leads to errors, as presented by the seven types of muda [3]. Since the majority of manufacturing processes finishes with grinding, it is highly important to safeguard the workpiece during this process as significant machining has already been applied beforehand. If there is an error or damage to the workpiece during grinding, the previous investment to is lost. A consistent process support by an adaptive AI-based framework gives a significant benefit for the improvement of process resilience and thus to the aimed minimization of rejection costs in manufacturing processes. The high demand placed on process control regarding dimensional and form accuracy is a key factor, which enhance the development of an assistance system for improved process control in grinding. With the support of an AI-based framework for predicting process results, currently prescribed time-consuming and cost-intensive 100%-physical inspections in quality assurance can be significantly reduced. The mass information stream (big data) from the acquisition of direct and indirect process signals, which results from the investigation of cause-effect-relationships in the grinding process, sets special challenges for the data processing architecture that needs to consider both online and historical data. Previous studies have shown that the amount of data generated from production processes in series production is already around 19.4 GB, or 12 billion data items per hour, when only the machine-internal data is considered. If additional, external sensors are used, this data volume for an exemplary fine blanking process quickly reaches ranges of

2.78 TB per hour [5], while acquiring data at frequencies between 2.5 and 1000 kHz, resulting up to 6.2 Gbit/s [28]. In previous work, force and current consumption, as well as acoustic emission signals have been intensively used to investigate process states, cause-effect-relationships and evaluate quality features of the process output. ZHIQIANG gives an overview about the application of AI methods regarding data mining and analytics in manufacturing processes [4]. As an additional process evaluation parameter, the wheel wear in grinding processes and especially the capability of monitoring systems to online measure the wheel wear turned out to be of significant value for the process outcome [6]. Thereby process state values measured by acoustic emission sensors, force sensors and current consumption were used to monitor wheel wear and to identify cause-effect-relationships between input parameters, e.g. wheel speed and feed rate, and output parameters, e. g. surface quality, geometry and form. Therefore, discrete wavelet analysis [7] and support vector machines have been applied on the provided data [8] for discretization of the process signal and outlining correlations between direct and indirect process signals.

Over the years multiple approaches both theoretical [9] and intelligent systems-based approach has been applied, with the aim to streamline and monitor the grinding process [10]. These studies have used different algorithms such as Fuzzy logic, ANN+ Genetic Algorithm and Hidden Markov Models among others. The majority of the previous scientific work provide a specific wheel-workpiece-pair based system, which implies that the system cannot be generalized. An extensive literature survey, do not show resilience of machine to singular/multiple sensor failure, i.e. if a singular physical sensor fails the whole system breaks down as outlined in the following Fig. 1.

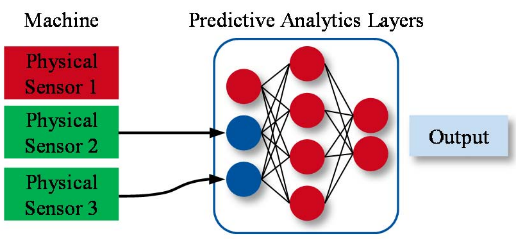

Fig. 1. Shows a breakdown/fault in physical sensor 1 leading to non-functionality of predictive analysis layer due to loss of input.

Since the modelling of wheel degradation during the process is a limiting factor [14] due to the semi-handmade production of the wheel and the alternating unique grain shapes, a monitoring and modelling system for degradation is inevitable for an effective process control. Fig. 2 shows the three different phases of wheel wear. The attempted techniques that model wheel wear have used technologies such as acoustic emissions [15], optical sensors [16] among others. These technologies are functional but do not provide for live monitoring but in most cases, rather a binary output i.e. whether the wheel is dull or not. A summary of the state-of-the-art research dealing with wheel wear is given in Table 1.

The remainder of this contribution is organized as follows. First a concept of an edge computing approach for the acquisition, sustainable storage and analysis of process data streams is presented. Second, an outlook on a demonstrating proof of concept using various data sources for a cylindrical grinding process is sketched. The acquired process data contains machine control states and external sensor data to monitor forces, coolant lubrication pressure and temperature. For the development of AI-applications to assist the grinding process, three main research objectives in the field of AI-application in grinding were identified: i) modelling dynamic wheel wear, ii) developing a generalized model independent of the wheel-workpiece-pair, iii) developing a resilient predictive layer for a graceful degradation. The dynamic wheel wear analysis is focused on the simultaneous surveillance of lubrication and force parameters and machine states. In the following sections challenges, methods and approaches for each research question will be discussed.

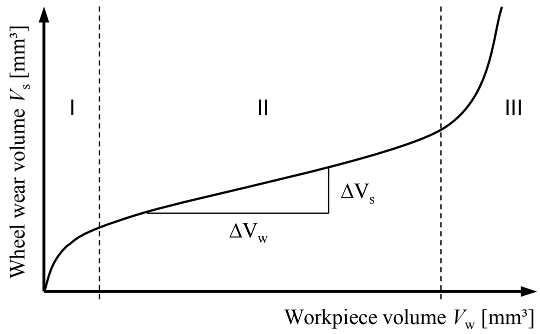

Fig. 2. Different stages of wheel wear, during the first phase (I) there is higher wear which can be attributed to the dressing process of the wheel, the second phase (II) is dominated by the grinding process conditions. The third and the last phase (III) is a failure phase where the wheel wear is so high that it should be avoided completely [14].

TABLE I. SUMMARY OF STATE OF ART RESEARCH ON WHEEL WEAR MODELLING ON GRINDING

Literature	Signals used	Machine Learning Models	Output
Maksoud & Atia, 2003 [21]	High response pressure transducer, Piezoelectric sensors	ANN	Sharp or dull
Liao, Hua, Qu & Blau, 2007 [22]	Acoustic Emissions	Hidden Markov Model	Sharp or Dull
Liao, Hua, Qu & Blau, 2008[13]	Acoustic Emissions	AdaBoost	Sharp or Dull
Hosokawa et al., 2004 [23]	Sound	ANN	4 wheel conditions

II. CONCEPT FOR AN AI-BASED FRAMEWORK IN GRINDING

The current section outlines the three mentioned researched objectives and describes the respective contribution for the planned concept for Deep Learning applications in grinding technology, which uses modern sensor data provision based on the Industrial Internet of Things.

A. *Modelling dynamic wheel wear*

Modelling dynamic wheel wear is an integral aspect in grinding as the surface quality of the workpiece and the geometric accuracy depends heavily on the sharpness and the condition of the wheel. By using a sharpened wheel the highest specific removal rates can be achieved, while fulfilling both, the surface roughness and quality requirements [24]. Thus, in-process monitoring of the wheel is a preliminary to predict the surface roughness and the surface thermal damage. With the intention to minimize high rejection costs, the use of AI-based methods for in-process optimization of the various influencing variables is necessary. Motivated by previous work, c.f. section 1, the combination of different sensors such as sound and acoustic emission in the modelling of wear using various machine learning approaches is researched.

For modelling the wheel wear, proper data sets that, in the best case, represent a continuous change of wear online during the process are needed. In future work, the possibility to scan and check conventional grinding wheels with non-ionising terahertz radiation, also called millimetre waves, for cracks and inhomogeneities will be researched. The approach follows the research hypothesis, that the precise detection and analysis of the global and local density distribution within the grinding wheel by means of millimetre wave technology enables the prevention of cracks due to inhomogeneities and to investigate the influence of the manufacturing process on the formation of inhomogeneities and thus on crack formation in grinding wheels. Scanning grinding wheels with terahertz radiation was lately enabled by an experimental setup by BeckerPhotoniks GmbH and used in previous work at the research institute [17]. In combination with the acoustic sensors and inline laser monitoring of radial grinding wheel wear and macrotopography, this could lead to a highly reliable wheel monitoring system. Upon integration of an online datastream of wheel wear, the information can be set in correlation with a model of the grinding wheel structure based on the volumetric composition according to Barth [18]. Following Barth, the macro- and microstructure of the dressed grinding wheel has a significant influence on the thermo-mechanical load collective in the grinding process and therefore also on the workpiece and surface quality. Thus, it is necessary to consider and integrate the knowledge about grinding wheel surface parameters into the machine learning environment of the framework system to be developed. If influencing variables are identified for a specific machining step, a real-time correlation between known input and previously unknown output variables can be generated in future steps. This knowledge can also be used to optimize machine tools according to the thermo-energetic design. At the same time, costs by not-in-order parts and unnecessary dressing cycles can be significantly reduced.

B. *Development of a generalized model independent of wheel-workpiece-pair*

For the development of effective monitoring systems, it is important to understand the basic wheel-workpiece relation independent of the specificity of the pair. To achieve this, it is necessary to analyse different wheel behaviour on various workpiece materials and geometries. Based on this data, a generic model can be developed and combined with the concepts of transfer learning to be fine-tuned to achieve the model performance for specific wheel-workpiece-pairs. The primary objective for developing these models is to predict the workpiece quality at the end of the grinding phase (spark-out), reducing the production and assembly cycle times by cutting down on the prescribed physical quality assurance to virtual quality assurance.

The implementation of such generic models requires methods that accurately model the process, but at the same time offer flexibility for fine-tuning the general model to specific use cases. Apart from classical time series analysis and prediction models, artificial neural network has proven to be promising in this area [27] and especially recurrent neural networks and convolutional neural networks, often used for human activity recognition, have already been applied in similar context for sensory data analysis. Both methods either could be used standalone for the analysis of the raw data signal, or combined with prior feature engineering pipelines [25]. In context of the research project, both methods will be implemented and evaluated to model the quality of workpieces for generic wheel-workpiece pairs.

C. *Development of a resilient predictive layer for graceful degradation of systems*

The concept of a resilient predictive layer is inspired by the ability of the human brain to be resilient in case of the loss of functionality of a particular region in the brain. It reacts against the lack of information or other faults, first by heightened processing of other sensory signals and secondly by allowing for relearning the lost functionality by several other parts of the brain [26]. In a sensor-based predictive model, this phenomenon is envisioned by exploiting the relationship between different sensors, for example, the values from force sensors are known to be related to the spindle load. Using this particular example and exploring other relationships between sensors, a set of virtual sensors whose output models the behaviour of a specific sensor, based on the input of other sensor signals, can be implemented. These virtual sensors can be thought of as a predictive algorithm which overtime learns from other sensors and act as a replica of an actual physical sensor in case of failure. These virtual sensors can, in case of failure of a certain physical sensor, kick-in to provide input to the actual predictive analysis model. Regarding the example of the spindle load and the resulting forces applied on the workpiece, if the force sensor fails, the input from the spindle load can be used to predict the force applied on the workpiece and thus the thermo-mechanical load, which the workpiece has seen. This information can then be used for the ongoing prediction of the workpiece quality and resulting wheel wear induced by the force. A schematic representation is provided in Fig. 3 (a) and Fig. 3 (b). Virtual sensors that model the behaviour of real sensor with a high accuracy also unveil that the sensors data may be redundant and can be discarded, or a weighting of various sensors data that reflect a cause-effect relationship can be determined by data-driven determination. In this context, the value of the actual sensor signal in comparison to the virtual sensor will be evaluated. Further on, the possibility of using these virtual sensors, once trained, as a way to detect anomalies in the physical sensor data, informing the operator of a possible breakdown of any physical sensor can also be explored.

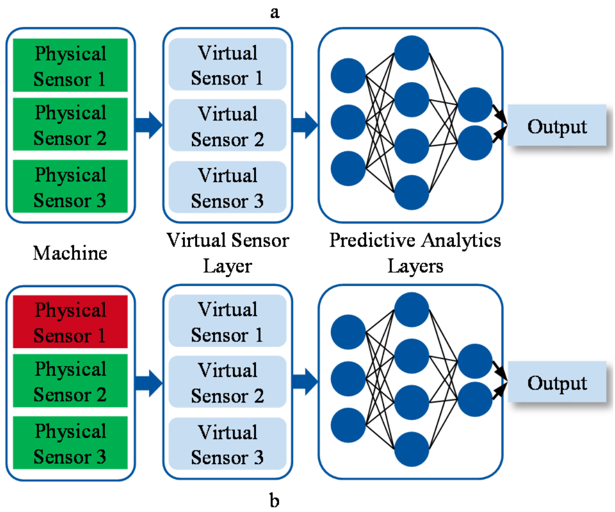

Fig. 3. (a) Shows the normal working phenomena of a physical sensor based predictive analysis. The virtual sensors keep training itself. (b) System detects a breakdown/fault in physical sensor 1, shuts down the training protocol and switches the input channel of the predictive layer from physical to virtual sensor 1 hence showing a level of resilience to system fault.

III. Experimental Grinding Setup

For an exemplary process to develop and test the conceptional approach based on modern AI methods and data analytics, a universal cylindrical grinding machine of type STUDER S41 at the research facility is used. In fact, different approaches for condition monitoring a grinding process exist. However, there is no solution in the production environment suitable for series production that enables data acquisition and processing as well as a real-time derivation of recommendations for actions. Further on, the experimental setup, the used process data sources and the sensor data acquiring hardware is introduced.

A. Data Acquisition

The S41 is provided by high precision axis drives with linear motors, direct driven wheel head with a resolution of 0.00005° and with a 30 kW high speed grinding spindle with a circumferential speed up to v_s = 209 m/s. Section 1 mentioned the necessity of process, machine and environmental data for a detailed analysis of the process. First, since the machine is operated in a research environment, it is additionally equipped with a quadruple KISTLER 9027C 3-component force sensor below the workpiece headstock for measuring forces and torques of the workpiece. A KISTLER 9129AA dynamometer is integrated below the external dressing unit. Fig. 4 shows the force measurement devices below the workpiece headstock (a) and the additional force measurement below the external dressing unit (b). Lubrication pressure and temperature is measured shortly before every cooling nozzle outlet and connected by an IO-LINK Master (MODBUS-TCP).

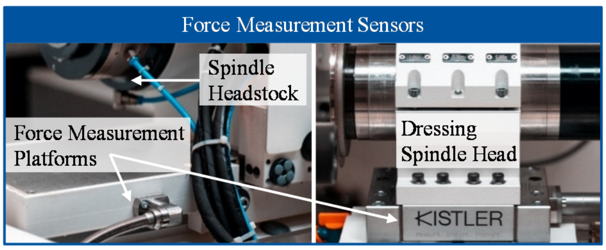

Fig. 4. Shows the mounted force measurement platforms inside the S41.

For the second data type, the PROFIBUS field-bus connectivity was read out using the TOOLSCOPE provided by CERATIZIT. The system is directly connected as a PROFIBUS slave device and reads the machine state data with a constant sampling rate of 100 Hz. The system reads axis positions, axis currents, spindle loads and machine status information and provides them with a time stamp. Furthermore, the TOOLSCOPE does not only allow data to be read out, but also opens a bidirectional interface to the machine control. In this way, changing parameters in the process control can be taken into account to dynamically adjust and optimize the process during the execution of a machining cycle. Third, environmental data is gathered by use of BOSCH XDK sensor devices that record outside temperature, humidity and vibration. The different sensors, representing the data sources, and their communication interfaces that need to be synchronized in their sampling rate and linked together into one data lake and data preprocessing architecture is shown in Fig. 5.

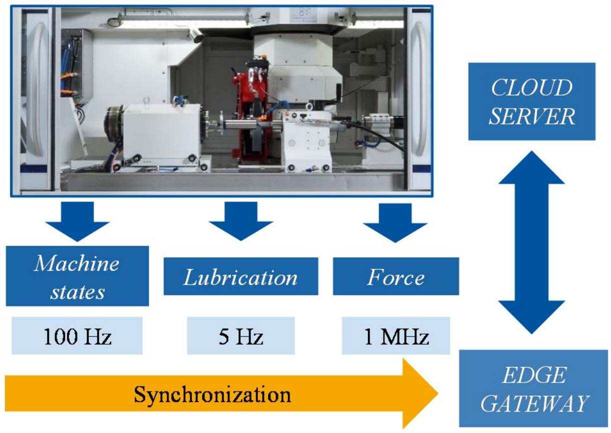

Fig. 5. Shows the three different process data sources synchronised at the edge to preprocess and provide the process data for deep analysis in a cloud server.

B. The Dataset and Preprocessing

The step of acquiring sensor data has been shown in Section 3.1. The data preparation, subsequently, is an initial step for machine learning model development, following the IEEE society [4]. The general objective of preparation is to select appropriate data for modelling out of the raw data lake and examine the data structure. Additionally, the following step, preprocessing, where selected data is refined to smart data is of significant importance before applying machine learning algorithms [19]. Part of the refinement is the enrichment with metadata. Indexed metadata enables specific filtering and exploration in the data lake. The state of research in Section 1 outlined certain requirements for a data preprocessing after the data acquisition has been taken place at the edge. First, the time axis has to be checked and sensor data of different sources need to be synced considering the time stamp. Second, errors and outliers have to be eliminated as long as they are not caused by process anomalies. This case is intercepted by alarm messages contained in the metadata. Outliers due to the measurement technology will otherwise deteriorate the quality of the machine learning model. To counter this, it is planned to use the Seasonal-Trend Decomposition Procedure Based on Loess (STL) [30], with median absolute deviation, to detect outliers. Third, missing data in the prepared data set need to be fixed, e. g. by interpolation. Fourth, scale and unit differences need to be addressed. Especially in the case of multi-national companies, a consideration of the metric and imperial system of unity in the data preprocessing is of enormous importance [20]. Exemplary data of an analogue cylindrical grinding process using the described data acquiring hardware are shown in Fig. 6. The plots show time-synchronized signals of the axis position, the axis current consumption and the spindle load as well as the associated grinding force in tangential direction. The manual analysis of the data logs already allows the recognition of various grinding cycles roughing, finishing, superfinishing and spark-out. The transition of the cycles is recognizable in all signals, so that a decomposition, feature extraction, selection and reduction is possible under consideration of the respective process cycle.

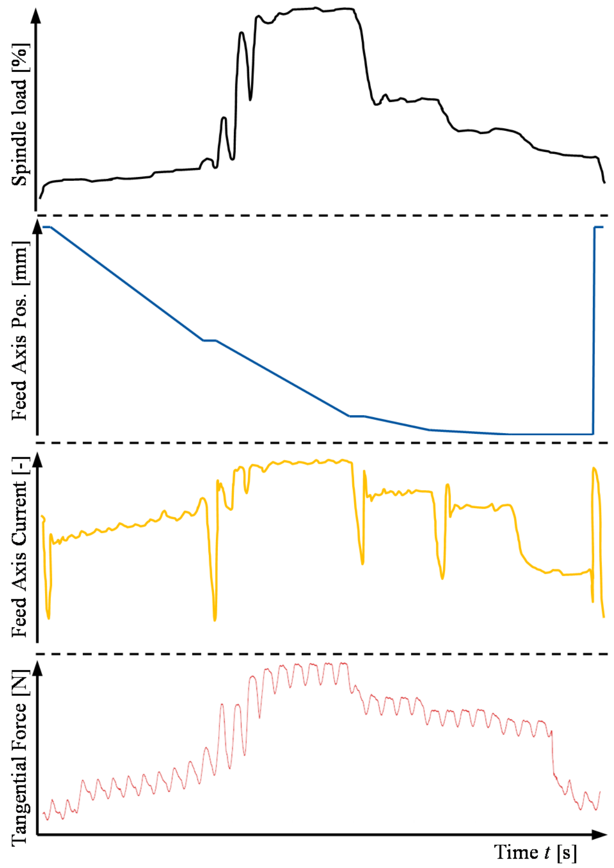

Fig. 6. Shows the spindle load, the feed axis position, the feed axis current consumption and the grinding force in tangential direction of an exemplary grinding process experiment.

In order to comply with the current requirements for the measurement chain for the application of machine learning algorithms and methods to predict the process output variables considering an amount of process input and state variables simultaneously, the mentioned framework for an edge-based assistance system in grinding will be set up in future work.

C. *The AI-based framework*

For an efficient improvement of the resilience in grinding processes, the introduced experimental setup, its data acquisition and pre-processing need to be set in an appropriate framework. Improving the resilience of the grinding process is closely related to an efficient manufacturing process with a constant quality at reasonable costs. Addressing quality, cost and time, the ability to withstand internal and external disturbances and hitherto unknown situations without lasting disruption, resilience in manufacturing, is a key factor for improving the polylemma of production, a topic addressed by the Cluster of Excellence "Internet of Production" at the RWTH Aachen University [29]. As part of this paper, regarding the derived research objective iii) linked to the AI-based concept in section 2, a framework to embed the virtual sensor approach into the manufacturing process data acquisition is introduced in the following paragraph. Figure 3 has already shown the function of the virtual sensor layer between the physical sensors and the predictive analytics layer. Thus, all available data of the internal machine states and of the external sensors is provided to the virtual sensor layer after an automated preprocessing step. Embedding the approach of virtual sensors in the data acquisition and analysis section of the AI-based framework for grinding processes enables the predictive analytic layer to generate process knowledge, e.g. dynamic wheel wear and thermo-mechanical loads on the workpiece surface for inline process monitoring. This knowledge is also stored into stream- and batch-processing architectures for an improvement of process models for an assistance system in grinding, which derives recommendations for grinding processes. The prediction of dynamic wheel wear as introduced in this paper represents a first deep learning application of the framework. As the connection of the virtual sensor layer is modular designed, the AI-based framework is highly scalable for other deep learning applications. Once process knowledge has been generated, process specific optimized parameter settings can be returned into the NC via PROFIBUS or OPC-UA connection. As a result, different, active applications can have parallel access to the virtual sensor layer, instead of accessing from a physical sensor data queue and thus positively influence the process result in a fail-safe manner.

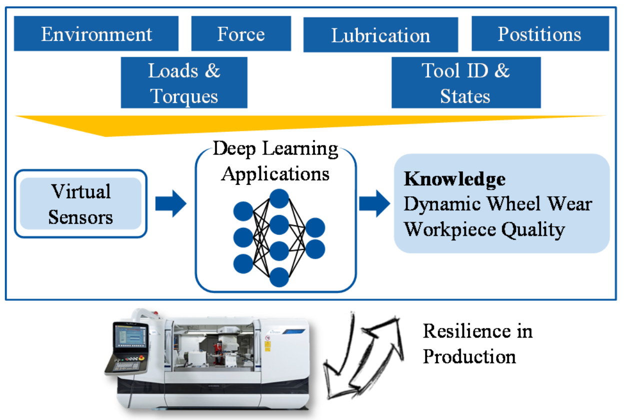

Fig 7. Shows the embedding of the approach of virtual sensors in the AI-based framework for increasing resilience in grinding processes.

IV. Summary and Future Works

Grinding is defined as a finishing phase of a manufacturing process, hence during the course of this high precision process, any error or slightest miscalculation on part of the operator may lead to significant losses both in time and cost of the overall production batch. To prevent these error or miscalculations, an AI-based framework for adaptive process control will be beneficial for cost reduction on the one hand and for improving process resilience on the other hand. To enhance the process monitoring, the online process signal analysis and the process resilience needed for both highest workpiece quality and minimization of quality assurance and rejection costs, this concept paper derived three research objectives for an AI-based framework for grinding processes.

The described test system equipped with a data acquisition system will be used to acquire versatile process data including varying wheel and workpiece material as well as different process setups during the grinding of workpieces known in the automotive industry. Based on the expected findings in the research environment, the customer can then use the acquisition of indirect process signals via modern machine controls to derive the surface properties, quality and shape tolerances of the workpiece. A cost- and time-intensive 100 %-inspection of all quality features, as is prescribed for safety-critical components, can thus be reduced to statistical process control (SPC) or the enabled virtual quality assurance. In the future, the knowledge generated by assistance systems enables technology metamodels to consider disturbance and influencing variables of the processes already in the planning stage itself. Another aspect for an outlook in the future is the automated variable control using the computer numerical control (CNC) interface, moving further from a recommender system based to semi-automated process to a full smart system for automated control. The concept of the virtual sensors and the concept of graceful degradation described above, if they perform to the expected objectives, can thus be expanded to a production line, where multiple sensors from multiple machines can be explored for relationships based on the output of one machine, which will serve as the input to the other.

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