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A fundamental approach for data acquisition on machine tools as enabler for analytical Industrie 4.0 applications

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Abstract

Decreasing ICT-costs propel connectivity and storage solutions for data generated, harvested and analyzed in machine tools. To acquire the necessary reliable, comprehensive and structured data for analytical applications, data from multiple sources must be acquired and combined. Many approaches for data acquisition either fail to cover all relevant data or cannot be put into action due to limited access on numerical controls. The following paper demonstrates the use of a multi-channel measurement application of a machine tool including its auxiliaries. The given approach was applied and verified on prototype machines. As a result, the application in current and future use-cases is discussed.

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Keywords: Machine tools; ICT; Data analysis; Data acquisition; Industrie 4.0; Efficiency improvements; Statistical analysis, Machine monitoring

1. Introduction

The total archived capacity of data worldwide has grown at a constant rate over the past years [23]. Table 1 shows the total worldwide archived capacity and its growth from 2010 to 2015 in Petabytes (PB). This development also applies to the manufacturing sector [1,24], where the term Industrie 4.0 characterizes the advent of connectivity solutions [32].

Data acquisition and analysis is used to improve the availability, performance and output quality of machines [31]. By the aid of data monitoring or statistical analysis, quality losses and component degradation can be identified on the machine [2,6,19]. In order to avoid the installation of machine- or application-specific sensors and measurement equipment, current approaches make use of the data provided by the machine tool's Programmable Logic Controller (PLC). However, data extraction from the PLC holds two major inconveniences: (1) Data acquired and made available for extraction only accounts for the components directly controlled by the PLC, which excludes the machine's auxiliaries, and (2) the extent and quality of data provided by PLC suppliers and machine tool manufacturers vary significantly and are therefore ambiguous [18].

Table 1. Total Archived Capacity Worldwide from 2010 – 2015 [23]

Year	Total Archived Capacity	Increase
2010	33,217 PB	-
2011	51,991 PB	+56,5%
2012	79,151 PB	+52,2%
2013	123,156 PB	+55,5%
2014	197,223 PB	+60,1%
2015	302,995 PB	+53,6%

Not all forms of data are suitable for statistical analyses, given their unstructured nature or the missing relation of input and output. To generate the necessary reliable, comprehensive and structured data for analytical applications, data from multiple sources needs to be acquired and combined. Many approaches for data acquisition and analysis are either limited by ambiguous and restrained data access on machine PLCs, or cannot be applied to different machine types due to machine-

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specific sensors. The following paper demonstrates the use of a multi-channel measurement of a machine tool including its auxiliaries. It is motivated by two considerations: (1) Downtimes of machine auxiliaries cause productivity losses in manufacturing systems similar to downtimes caused by integrated machine components, and (2) monitoring systems need to be deployable in heterogenic machine parks comprising different machine tool and PLC types, in order to acquire the necessary data for monitoring and analysis applications. The proposed approach was applied and verified on prototype machines.

2. State of the Art

2.1. Data-driven Modeling and Analysis in Machine Tools

The exploitation of data in manufacturing enables many applications along the value stream [1,8,24]. For machine tools, particularly the aspects product quality and process performance can be impacted by data driven optimization [31]. Blaser et al. [2] propose a system which allows to model the deviations of the Tool Center Point (TCP) and the table of a 5-axis machine tool. As a consequence, a compensation algorithm is applied online after a reference measurement. The necessary data is generated by two temperature sensors, a touch probe and a direct communication interface to the machine PLC. Lenz et al. [21] suggest the combination of machine tool control, tool management and Enterprise Resource Planning (ERP) or Manufacturing Execution System (MES) data to obtain improved tool wear models. Haas et al. [13] introduced an iterative learning control for machine axes in order to reduce tracking errors in contour shaping. Overall, these approaches share the common underlying principle of data fusion from numerous sources in order to improve operational efficiency.

2.2. Combination and Integration of different Data Sources

The increasing relevance of data for statistical modeling (“learning”) purposes in manufacturing systems is especially emphasized by Cochran et al. [3]. They introduce considerations for future data use already in the design phase of manufacturing systems. The subsequent increases in volume, variety and velocity of data pose raises issues: Aside from privacy and legal concerns, the extraction of meaningful information from different heterogeneous sources, the varying data quality according to its sources, and finally the encompassing scalability of solutions remain important challenges [31].

The integrated use of data and its combination from multiple sources not only applies to manufacturing systems, but also to multiple machines spread across different localities. Collecting and combining their data for modeling purposes is also referred to as fleet learning [18]. To overcome previously stated challenges, high-quality high-quantity structured data needs to be available. In the context of machine tools, Wang and Alexander [31] only count spreadsheets, relational databases and ERP or MES data to the forms of structured data. Semi-structured data are XML files, data from standard machine components and sensors, as well as machining log time-series. Their form does not comply with relational databases, but they are characterized by tagging or marking allowing to be decoded into a more structured form. Machine PLC data can be either category: Categorical and structured data usually sent to MES systems, as well as semi-structured data in machining logs.

2.3. Data-Use for Prognostics and Health of Machine Tools

Particularly the importance of industrial big data analysis for Prognostics and Health Management (PHM) in manufacturing systems is described in several publications [3,8,17–19, 22,27]. For PHM approaches in machine tools, data requirements go beyond structured and semi-structured PLC data: Differences in data structure and data quality provided by different PLC hinder the transfer of lab cases to industrial applications, and PLC data does not cover all relevant aspects for most published approaches [2,13,14,21]. This notion is confirmed by Lee et al. [18], who identify a low utilization of available information due to the lack of adaptability of specific solutions. The lab trained models in general exhibit poor performance due to neglected external influences of industrial applications, such as varying load patterns and temperatures. As a result, it appears reasonable to combine live data from different machines under various conditions instead, to create self-aware re-training models. This includes a vision of a fleet of machines contributing data to train and improve models which in return serve all connected entities. Lee et al. [18] also state that the reason for this application still awaiting its realization is the low adaptability of learning algorithms for PHM purposes. They equally criticize the inherent loss of large amounts machine fleet data without making any use of it.

Table 2. Types of freely available PLC machine data

Structured data	Examples
Machine State	Ready, Run, Manual Setup, Interruption by M0 or M1, Finished, Error, Emergency Off, Missing Material
Specific Errors	Coolant, Tool Break, Scrap, Hydraulics, Pneumatics, Drives
Parts Counter	Good Part, Rework Needed, Scrap, Individual by M2-M89
Cycle Counter	Actual Time, Allocated Time
Override State	0% or 100%
Fabrication ID	Fabrication Order ID, Part ID, NC Program ID
Components Running	Main Spindle, Counter Spindle, Tool Change
Infeed	Infeed Rate per Channel
NC Run Type	Auto, JOG, INC / INC rate (10/100/1000/10000)
Machine State*	Manual, Preparation, Maintenance, Technical Default, Waiting for Material, Waiting for NC Program, Waiting for Measurement, Waiting for Operator, Waiting for Tool, Waiting for Fixture

*machine tool manufacturer specific (not commonly available)

Most data usable for PHM approaches is not available in a structured manner, but needs to be extracted from logs and time-series, under the condition of an appropriate resolution and sampling rate. Table 2 provides an overview over the different data categories made available by a commonly used

Sinumerik 840D via synchronous communication. Other data, such as machining or event logs, are available by asynchronous protocols. The availability, accessibility and specification of these logs depend on the machine tool manufacturer and are not standardized. Likewise, the informational content for PHM applications is low. To make use of this data, it needs to be put into context or enriched by additional data. Additionally, it can be used in order to exploit the informational content of other semi-structured data, such as machining logs.

Additional information, such as component energy consumption, axe positions and spindle speeds, are provided by some NC manufacturers. These interfaces are mostly of proprietary nature, of which some can be mapped to standardized protocols such as MT Connect or OPC UA, requiring proprietary machine tool manufacturer knowledge. However, neither the resolution, sampling rate, transfer rate, data type nor reliability are standardized, and therefore have to be tailored to specific needs and verified by additional measurement equipment. For instance, Fanuc controls deliver energy consumption rates in percentage [%] units, whereas Siemens controls display absolute values. The use of energy consumption values is, similarly to machining logs, highly ambiguous and subject to control dependent or manufacturer dependent standards. However, for modeling and monitoring product and process quality, a combination of both structured PLC data and semi-structured machining logs, to combine part IDs, machining logs and subsequent quality analyses, is needed.

For general monitoring and specifically PHM applications, the currently available data generated and made available is not sufficient, as it (1) depends on both, the machine and the control manufacturer, whether data is available in the necessary extent, and (2) applications cannot be designed for different machine types due to differences in the form and quality of data provided, even if standardized protocols are used.

An additional requirement is the data type and quality sufficiency for the desired application, regardless of the protocol or control type. Many approaches either rely on other data sources, or alternatively combine standardized protocols with additional data sources. Both approaches are suggested in many recent research publications (e.g. [20,26,28,30]). This observation implies that data provided by controls is neither sufficient nor does it allow for scalable application of PHM and other analysis solutions.

2.4. Monitoring Approaches of Machine Tools and Components

Monitoring approaches can be organized in the following four categories: (1) Proprietary applications based on standardized protocols, (2) proprietary applications based on proprietary protocols, (3) interoperable applications based on standardized protocols, and (4) interoperable applications based on proprietary protocols.

An example for a proprietary monitoring approach based on a standardized protocol is the Remote Machine Monitoring System (RMMS) by machine tool manufacturer DMG Mori Seiki [25]. It is an MT Connect based application used to determine the machine's operating status, detect and report machine failures, and make it accessible [4].

The FANUC MT-LINKi is a monitoring solution based on the FANUC FOCAS communication interface. It therefore corresponds to proprietary applications based on proprietary protocols. It gives access to more detailed machine information, such as feed rates, spindle and servo loads, as well as component temperatures and overrides. Even if originally developed for the FOCAS protocol, FANUC has also opened its monitoring approach to third party machines via OPC UA interfaces [7].

Interoperable protocols based on standardized protocols mostly originate from within research groups and are therefore diverse. Shin et al. [28] propose to combine Step-NC data as a cause data set with MT Connect machining logs as a result data set. It is used to train a neural network to predict energy consumption for specific parts based on the Step-NC input. The model was applied to a single machine tool type only. Lei et al. [20] suggest to extend the MT Connect model in order to accommodate sophisticated on-machine quality measurements. This allows for an inclusion of both machining and quality data within the machining system, facilitating monitoring and cause-effect relationship measurements. In 2010, Vijayaraghavan & Dornfeld [30] demonstrated a laboratory application of an MT Connect based energy monitoring system, which can be used to identify patterns in energy consumption time-series. The detected patterns are manually allocated to events that occurred on the machine's spindle, such as idle states, expected and anomalous spikes.

The examples cited all demonstrate the necessity to harvest data in addition to the information provided by the standard interfaces for monitoring or PHM tasks. Moreover, they focus exclusively on integrated machine components. However, the communication between auxiliary and machine is generally realized via release signals provided by the PLC, only in rare cases they are directly controlled by the machine's NC. This makes the extension of monitoring and PHM tasks even more cumbersome, given that an inclusion into current standard protocols needs to be integrated in the proprietary auxiliary control. This issue cannot necessarily be fixed by a mere standard extension, given that auxiliary controls often are rather simple logic controllers, which are not intended for complex control and communication tasks. Unexpected downtimes of auxiliaries can incur the same productivity losses as defaults on main machine components.

2.5. Energy Consumption based Machine Monitoring Approaches

Recent research has demonstrated different approaches, which are either specific in their application, the machine or the control type that they apply to. Altogether, the current standardization efforts do not cover all relevant parameters for a complete data scheme of all monitoring aspects and PHM functionalities across an entire machine including auxiliaries. The energy consumption measurement is a common starting ground, which can be observed across multiple approaches:

Johansson et al. [14] proposed the "Green Condition Based Maintenance" principle in 2014. It collects operating and socalled fingerprinting data, which is a pattern of energy consumption patterns for specific operations or operational modes. Via Motor Current Signature Analysis (MCSA), currents for components are registered and analyzed via e.g. a Fourier analysis. A subsequent publication even stresses the possibility of calculating a Remaining Useful Lifetime (RUL) estimation [15]. To achieve the necessary resolution and sampling rate, additional sensors were installed on the drives of the components. The model was only examined for a test bench with a drive on a linear ball screw guide.

Mourtzis et al. proposed a framework for an on-machine sensory system in 2016 [26], which includes data acquisition of spindle and axis motor currents and spindle RPMs. This data is combined with manual operator input data via a supplementary Human Machine Interface (HMI). It is described as a Condition-Based Preventive Maintenance (CBPM) approach, which is yet to be validated. The model comprises only main machine components of a five-axis milling machine, without auxiliaries.

Emec et al. addressed the advantages of minimal-invasiveness and therefore enhanced retrofit capabilities for monitoring applications in 2016 [5]. Their proposed concept foresees energy consumption measurements at the main power supply to match it with other event-based data. For standard products, energy measurements can be used to detect outliers in consumption patterns.

Gontarz et al. have proposed a multi-channel energy consumption measurement and monitoring system [9–11]. The main focus lies in the assessment of component energy consumption behavior, the data acquisition is carried out via a multichannel measurement system. The system is not limited to power measurement, but can be extended by other synchronized sensors. The experience of more than 150 machine tool analyzed with SIGMAtools LLC suggests an applicability of the system also to other domains, especially general monitoring and PHM applications.

3. Concept of a Data Acquisition System (DAQ)

For the introduction of monitoring and measurement applications, it is required to define the level of application. Gontarz et al. [12] suggest to distinguish between three hierarchical levels, according to Fig. 1. L1 defines the Enterprise Level, such as Procurement (P), Logistics (L) and Manufacturing (M). On the intermediary layer (L2), the manufacturing activity for instance is subdivided into different processes or workshops, e.g. cutting or grinding. On the lowest level (L3), each machine is described independently per process. The following approach is defined as bottom up and focuses on L3 to acquire all related date on the component level. This enables full flexibility for related upscale use cases.

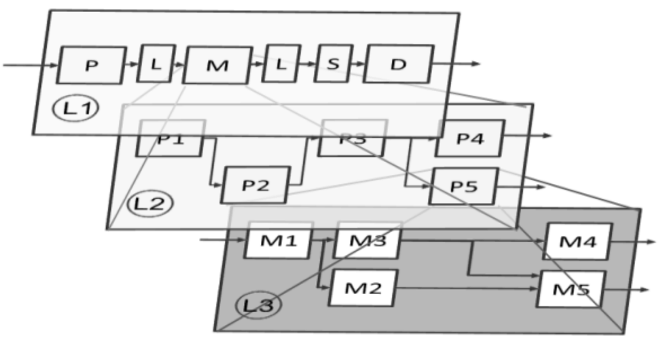

Fig. 1. Levels of Application for Measurements and Monitoring [12]

3.1. Required Elements for a DAQ

As machine tools are complex, individually configured mechatronic systems, a data acquisition by a Multi-Channel system including peripherals is required. The DAQ needs to deliver a complete, synchronized, accurate data set of all relevant machine tool components in all possible machine tool modes of a high sampling rate, allowing to apply different analytic approaches, such as energy efficiency, process efficiency, component health, maintenance requirements and reconfiguration potential. In terms of acquisition schemes, all relevant components and auxiliaries need to be covered. Additionally, all data provided by NC and PLC, alternatively trigger signals from the PLC, can be accommodated.

The multichannel measurement and monitoring system according to Gontarz et al. [10,11] measures the power consumption of each relevant component. Together with the power measurement, the DAQ system must cover the component control dependency based on all possible machine tool modes including all active machine tool components. The relevance for the consideration of components and modes is defined by ISO 14955 [29]. Fig. 2 shows the performed machine tool measurement for a test work piece and based on the test machine tool in standard configuration. The different sectors represent the power consumption of different relevant machine tool components, including all electrical components, compressed air and media flow from external sensors. The required output sampling rate strongly depends on the respective use-case: To detect component behavior for energy and process efficiency analyses, an output sampling rate in the region of 10^0 Hz is considered sufficient [11]. For PHM applications, output sampling rates of 10^2-10^4 Hz are required [5,15]. In order to fulfill the Shannon-Nyquist-Theorem, acquisition sampling rates therefore need to be in the higher 10^4 Hz regions.

For the connection with the next highest enterprise level (L2 in Fig. 1), data transmission via structured files (XML, CSV), open communication standards (OPC UA), and a direct access for visualization, analytics inputs and configurations, interoperable with all devices (HTML5), are required.

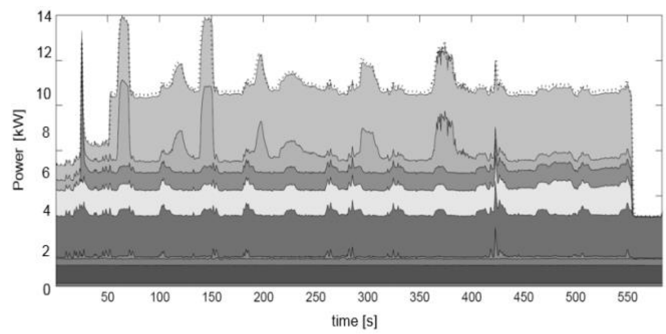

Fig. 2. *Measurement of Power during machine state PROCESSING [29]*

3.2. General Component Behavior

The considered machine tool components represent main components, e.g. spindles – controlled by the NC, as well as auxiliaries mostly controlled individually or via the PLC. The energetic behavior of machine tools components and subcomponents, e.g. drives , pumps or cooling devices, can be classified in three different power consumption behavior modes [9,10]. These modes are:

- **Constant:** Components are either on or off with a fixed power level within the measurement accuracy of +/- 5%. The classification is made according to Gontarz [10].
- **Controlled constant:** The energetic behaviour of Controlled constant components during operation mode can be separated into three phases. Those phases imply the start-up and switch-off peak.
- **Variable:** Variable components, e.g. spindle or axis, are represented by a process-dependent and heterogeneous energetic behaviour.

Other energy flows, such as compressed air, are classified according to the component characterization as shown above. All relevant components must be considered either by measurement or simulation.

3.3. Monitoring system architecture

Based on the component behavior classification, the information sources are selected accordingly. In general, a five-axis machine tool requires 15 to 20 measurement points, representing essential machine tool components for a detailed measurement. Therefore, data acquisition can lead to a certain implementation effort. For cost saving reasons and adaption of the DAQ strategy, different information sources on the machine tool level can be defined, without compromising data accuracy.

An overview of all data sources considered by the DAQ is provided in Fig. 2. It distinguishes between external sensors proprietary to the DAQ, internal accessible sensors of the machine tool, and virtualized sensors (‘Simulation’) used for particular use-cases. The components are aggregated by type of function in order to allow for facilitated analysis.

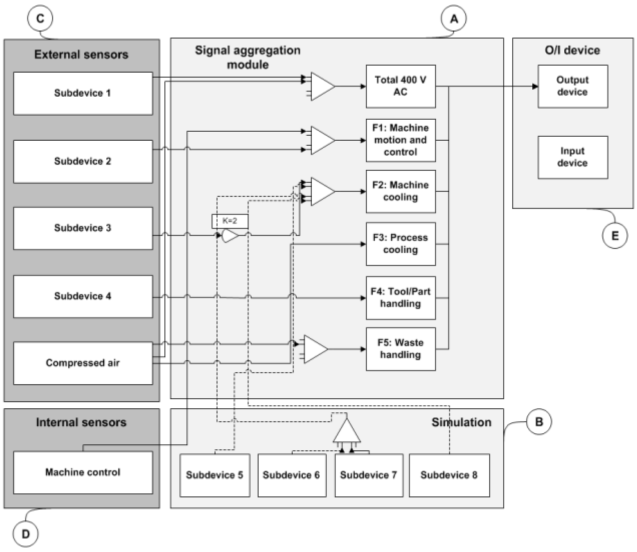

Fig. 3. Data Acquisition Scheme, composed of Internal, External and Virtualized (Simulation) Sensors, p.158 of [9]

3.3.1. Internal Sensors

According to the requirements related to cost saving, accuracy, and reliability, all available and accessible internal sensors within the machine tool control are used in the proposed approach. For instance, the required power information is available from the drive controller as part of the drive control loop and internal reference system variable. This allows accessing component information on control-dependent machine tool components, e.g. spindles, axis, or generators.

3.3.2. External Sensors

External sensors are required for variable machine tool components, and where internal sensors are either not accessible, or fail to reach the required accuracy. External sensors are also needed for internal calibration and verification in combination with the PLC controlled simulation and internal sensors.

3.3.3. Virtualized Sensors

For constant or controlled-constant components, a virtual measurement channel, based on a PLC controlled I/O model can be defined, sparing the expenses of an additional sensor integration. For the highest accuracy, either a detailed component measurement or a physical model can be applied. The simulation needs to consider relevant component states, e.g. start-up phase, constant phase, and switch off phase. The input for these models are given by the PLC state.

3.4. Use-Cases and Application Fields of the DAQ

The application of this measurement approach leads to use-cases, related to the evaluation and optimization of production processes and machine components. Based on the acquired use-case, the analysis or the raw and aggregated data to be analyzed are transmitted to the respective systems or key operators.

An example for a relevant use-case based on a simpler version of the monitoring system is demonstrated in [16]. It describes the DAQ used to monitor resource consumption on the shop floor and its integration into the manufacturing control environment. This approach shows that a key element based on the acquired data is the accurate quantification of the component behavior on the shop floor, machine tool level [8,15,17] and its components. The approach shows further that, based on the component behavior knowledge, different DAQ architecture optimizations for cost saving and implementation effort can be applied. The DAQ can be considered a crosslink between the machine component and the manufacturing control instances, such as the MES.

An additional application which has currently been verified, is the determination of degradation status of consumables in a machine auxiliary. Based on a test cycle performed by the component, critical deviations can be measured via the DAQ in order to determine the condition of the consumables.

4. Conclusion and Outlook

It is clear that without data, optimization or related use-cases are either not applicable or inaccurate. The rise of available data and applications to perform analyses in manufacturing drives the need for comprehensive monitoring solutions. In order to harvest the necessary data from multiple sources and various component types, a data acquisition system to cover all relevant aspects and components is necessary. The given approach describes a system encompassing data acquisition and analysis, in order to improve the availability, performance and output quality of machines. It makes use of data monitoring allowing for statistical analysis to detect efficiency losses and component degradation. The description focuses on the structural and application-dependent aspects of the DAQ. The DAQ architecture is fully described and matches a set of industrial requirements. It can be applied to diverse use cases, given that the data requirements are fully defined a priori.

The possibilities for analytical applications range from pattern recognition over training of neural networks to frequency analyses. However, a clear procedure and definition of a use case must be given to define the required data. The proposed DAQ can is a key element to fulfil a defined and envisaged analytical application and related I4.0 use case. The full configuration of structural and analytical parts of the DAQ is always related to the final use case. Preliminary research and the first applications of the DAQ reveal that it fulfills the requirements, and that it can be used for various applications on machine tool components and auxiliaries.

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