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A development approach for a standardized quality data model using asset administration shell technology in the context of autonomous quality control loops for manufacturing processes

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Abstract
In modern markets, increasing quality requirements require high performance quality assurance processes which guarantee the fulfillment of these requirements sustainably. The quality assurance must therefore be able to take targeted countermeasures in the event of deviations. It is becoming increasingly decisive to achieve quality with minimum resource expenditures, increasing the importance of quality control loops. Currently, however, a great deal of manual effort goes into the design and implementation of the mostly knowledge-based control logics due to the heterogeneous data landscape and the resulting data preparation processes. Autonomous quality control loops represent a new development and are intended to provide an efficient and data-based approach to setting up quality control loops. According to the "plug and play" principle, the control system should be operational with a minimum of resources in order to enable precision engineering. Prerequisites for such autonomous systems are homogeneous data structures and models for the holistic representation of quality data, which make individual data preparation processes obsolete. In addition, individual process models must also be replaced by suitable data-based, learning modeling methods. In the following approach, the fundament for a holistic quality data model is developed on the basis of various interviews with diverse companies active in the field of metal-cutting and additive manufacturing. The data model is represented using the Asset Administration Standard of the I4.0 platform. In addition, machine learning approaches in the area of machining and additive manufacturing are analyzed for the general modeling of the correlation between process parameters and the quality result, in order to be able to develop a holistic concept for autonomous quality control on this basis in the next step.

Industrie 4.0, Data Model, Quality Data, Quality Control Loops, Correlation Analysis, Machine Learning

1. Motivation

Major challenges facing modern production include volatility-increasing trends such as increasing product individualization and difficult-to-predict demand scenarios that influence unit quantities and quality requirements. Accordingly, companies can only survive the unforgiving competition if they confront the aforementioned change scenarios in an agile manner with efficient and reconfigurable production systems that are capable of efficiently enabling immature processes. This should shorten ramp-up phases and enable newly configured production systems to start up quickly [1, 2].

In order to be able to control quality requirements efficiently and with minimum scrap production, a holistic quality management in the company is indispensable [3]. An important part of quality management is the precise recording of defined quality characteristics of manufactured products. Today, data acquisition still often takes place in remote measuring rooms, which entail a high dead time when it comes to catching drifting quality characteristics and readjusting processes. Accordingly, it makes sense to bring measurement technology closer to the manufacturing process and to increase the degree of integration. A distinction is made between measurement technology that is remote from production, close to production, inline, machine-integrated and in-process [4]. Quality control loops built on this basis are nowadays implemented with a high manual effort and exhibit static characteristics. For effective and short-cycle control, however, the control dead time due to the long data acquisition paths and the manual effort required to set up quality control loops must be minimized [5].

The transformation scenarios mentioned before force quality control systems to adapt to reconfigured production systems and dynamic product portfolios. This requires measurement technology with a high degree of integration, generic as well as adaptive quality control logics, and a high and, above all, standardized data availability. We define ***Autonomous Quality Control*** as a quality control concept considering these factors.

2. Autonomous Quality Control Loops

Quality control loops are closed-loop control systems which, on the basis of measured quality and/or process data, calculate process parameters of the considered, feature-generating process by optimizing the quality characteristics by means of an implicit or explicit logic [6]. For the uniform description of quality control loops and their suitable decomposition, the analogy to control loops from measurement and control technology is established. For the exact structure of the analogy, reference is made to the work of Schick *et al.* [5]. Figure 1 shows the schematic structure of this control loop.

The center of the quality control loop is the quality controller. It contains implicit or explicit logic that describes the correlation between the control variables of the process and the quality result. With this correlation, the quality control is obtained for the optimization of a quality function $Q(P_1, P_2, \dots, P_n)$, which can depend on various parameters [6]. Formally described this means

$$P_{opt} = \begin{pmatrix} P_{1,max} \\ P_{2,max} \\ \dots \\ P_{n,max} \end{pmatrix} = argmax(Q(P_1, P_2, \dots, P_n)) \quad (1)$$

where a higher value for the function $Q(P_1, P_2, \dots, P_n)$ would correlate with a better quality result. The vector P_{opt} describes the globally optimal parameter combination for improving the quality result.

Depending on the complexity of the system under consideration, the mathematical/physical modeling for the design of the quality controller requires a great deal of manual effort. In addition, in almost all cases the input data used must be pre-processed in order to make them available to the controller in a suitable manner [7].

This is where the concept of ***Autonomous Quality Control*** comes in: Autonomy is to be achieved through data-based and, if possible, process-independent modeling for correlation description as well as standardized provision of quality and process data. This requires a uniform description for the holistic mapping of quality data. Such a data model makes it possible to deploy quality control loops much more efficiently, to adapt process parameters directly on a bilateral basis, and at the same time to transfer logic that has been developed to other systems with little effort.

2.1 Quality Data Model based on Asset Administration Shell

In recent times, there have been significant advancements in data collection and utilization techniques that have enabled the adoption of holistic data models in product and production development processes aiming more efficient data exchange. This has been made possible by the introduction of open standards for model-based definition, such as STEP AP 242 and QIF 3.0. These developments have equipped engineers with a wealth of data to enhance the development and optimization processes [8]. The QIF (Quality Information Framework) 3.0 framework was developed by the Digital Metrology Standards Consortium (DMSC TM). It is a data exchange standard that is used in the manufacturing industry to facilitate the sharing of quality measurement data between different software systems and applications. The QIF 3.0 Framework allows seamless transfer of data between different software tools and applications that are used in the design, manufacture, and inspection of products. Specifically, it defines a standardized set of XML-based data models, schemas, and vocabularies that are used to describe various aspects of quality measurement data, such as measurement features, measurement plans, measurement results, and statistical process control data [9].

The STEP AP 242 standard focuses more on design data and does not regard inspection information like QIF [10].

In addition, commercial CAQ software exists that is closed source and not publicly accessible. Accordingly, the important criterion of interoperability is not given.

The concept of the asset administration shell (AAS) is suitable for building such a standardized and holistic mapping of quality

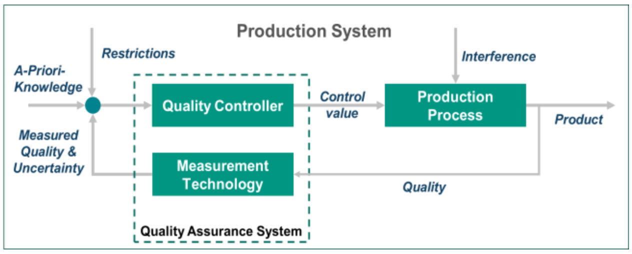

Figure 1: Quality Control Loop (wbk – Institute for Production Science)

too and offers various advantages compared to conventional approaches of data modelling. The AAS technology is of outstanding importance in the Industrie 4.0 landscape, as it is seen as the cornerstone of interoperability in this context [11]. Both the information model and the interface of the AAS are standardized and can handle all heterogeneous systems present in the industrial environment [12]. Because the AAS is an abstraction that provides a common structure for plant-related information and a common consensus for exchanging that information [9], it enables interoperability among the production infrastructure consisting of different technologies [11]. Currently there is no approach which models quality data in the context of providing data more efficiently for quality data based applications like quality control loops. The great potential behind the usage of AAS technology, especially regarding interoperability, scalability as well as standardization potential across various productions systems is to be uncovered within the framework of this scientific elaboration.

In the following, the relevant components will be determined. The structure of the Asset Administration Shell is specified by the Federal Ministry for Economic Affairs and Climate Action (BMWK) [13]. The aim of efforts in this area is to create a common communication consensus on the base of which information about assets and I4.0 components can be exchanged in a meaningful way [13]. In addition, this defines the structure of the data modeling and all its components. *Figure 2* shows the respective components in a UML diagram. In this context, the quality data model can be regarded as an asset in its own right, consisting of various submodels. The I4.0 platform defines an asset as: "physical or logical object owned by or under the custodial duties of an organization, having either a perceived or actual value to the organization" [13]. The logical decomposition of the data model takes the form of submodels that reside in the AAS. Submodels are defined as "models that are technically separate from each other and are contained in the Asset Administration Shell" [13].

In order to identify submodels of quality, interviews were conducted with quality departments of 4 different, manufacturing companies as part of a practice-oriented approach. The aim was to determine from a practical perspective which data are relevant in the context of quality assurance processes and quality control systems and how these data can be made available:

First, it makes sense to divide quality data into quality features. Since resources used (e.g., lathes) and the respective processes (e.g., milling) must also be taken into account for holistic quality control, these ***quality features*** should be linked to

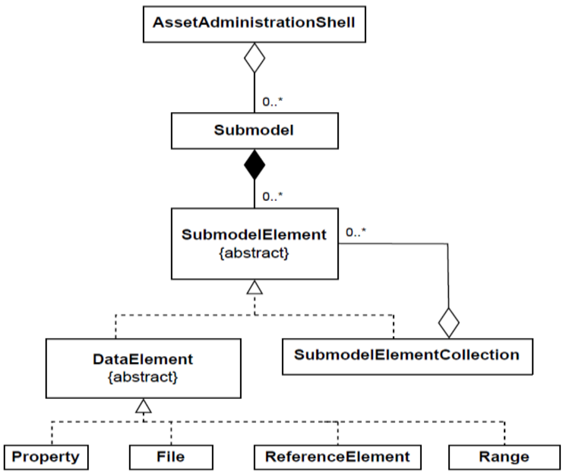

Figure 2: Components and hierarchy of the AAS [1]

manufacturing steps. Each manufacturing step that is passed through to create a product generates quality characteristics that must meet certain requirements. In the level below, all features are to be stored with the respective required information. These can be divided into three categories: First, Target-State. Second, Actual-State and third, Specifications for the metrological recording of the quality feature

<u>Target-State</u>

The target state of a quality characteristic is determined on the basis of a ***nominal feature definition*** which consists of a value and a unit. Since no manufacturing process is 100% accurate, relative or absolute ***tolerance limits*** are also required. A ***characteristic type*** (e.g. dimensional tolerance or form tolerance) enables a better classification of the quality feature.

<u>Actual-State</u>

The actual condition of the quality feature includes first of all the recorded ***actual value*** of the measurement. Furthermore, it should be recorded at which ***time*** the measurement was carried out, which ***part number*** the manufactured part has and additionally whether the ***characteristic*** is i.o. or n.o..

<u>Specifications for the metrological recording of quality features</u>

In order to avoid a 100% inspection, the principle of representative sample analysis is defined within the concept of statistical process control, which most manufacturing companies make use of. In this process, defined samples are taken from the manufactured products and conclusions are drawn about the process based on these partly made measurements. The basic prerequisite for this is a controllable and stable process [14]. For a holistic quality data model, it is important to be able to map which ***sampling cycle*** and which ***sample size*** were defined. Apart from this, it has to be clear which ***inspection tool*** was used to carry out the measurement. Furthermore, it should be possible at this point to store further details about the measurement procedure. This can include, for example, measurement strategies and raw data from measurements with the coordinate measuring machines. At this point, however, a ***further specification*** is to be renounced for the purpose of preservation of the genericity in the data model. The result of these considerations is *Table 3*, in which all already described components of a quality data model are categorized.

Table 1: Components of a holistic quality data model

Target-State	Actual-State	Measurement specifications
▪ Type ▪ Nominal Value ▪ Upper Tolerance ▪ Lower Tolerance	▪ Actual Value ▪ Time of Measurement ▪ Part Number ▪ Feature i.O./n.O.	▪ Measurement Equipment ▪ Sample Size ▪ Sample Cycle ▪ Further Specifications

2.2 Data-based Correlation Analysis for Model Approximation

A prerequisite for autonomous quality control is the efficient, data-based correlation analysis of the cause-effect relationship, in particular between process parameters and the resulting quality outcome. As already described, conventional quality control loops require a lot of manual effort to define this relationship mathematically and/or physically by incorporating explicit domain knowledge. ***Machine learning methods*** such as artificial neural networks are particularly suitable for this purpose as a form of implicit function approximators. Here, only the procedure for learning is specified without introducing explicit knowledge about the process [15]. Challenges are the acquisition of a ***good database*** and also the computational effort. In most cases, several parameters simultaneously have an influence on the resulting quality result [16].

In the context of these considerations, 3 existing, representative approaches with different focuses will be investigated that identify data-based correlations in manufacturing processes and build an approximated model based on these correlations. The state of the art shall support to better evaluate the performance of ML methods in this context and to identify which challenges take space in this context.

Teutsch and Schenk [7] present an approach in their article "Quality Data Driven Production", which deals with the data-based control of a milling process for the production of aluminum wheels. This is intended to cover different wheel types and basically represents a more generic approach to quality control for milling processes. 5000 data sets for 30 different wheel types were analyzed. Each data set consists of 81 geometric nominal and actual values. The goal is to predict the wheel quality at the end of the process based on different data analysis methods and prediction algorithms, among others consisting of an intelligent approach built on a neural network. It enables the prediction of a wheel-specific diameter as a function of the process temperature. An important finding from the observations is that data ***outliers*** significantly degrade the prediction quality, while creeping changes in process parameters can be well handled. Furthermore, the analyses show that prior ***filtering*** of outliers is of great importance to make the forecast accurate and reliable.

In any case, tool wear correlates directly with the quality result of the manufactured product. An interesting approach to this was published by Wu *et al.* [17]. It deals with the prediction of tool wear during milling. Unlike classical approaches in this area, which usually make use of neural networks, Wu et al. resort to modeling using random forest (RF) techniques. The results are evaluated and compared with a feed-forward back propagation network and a support vector regression (SVR). The results are particularly interesting for this work, since the best possible process modeling quality is to be achieved and ***the comparison between ML-Methods*** provides performance statements about the respective models. The training data was generated in advance in an experiment by Huang *et al.* [18]. Here, for all three procedures, 2/3 of the data was used for training purposes and 1/3 for testing purposes. The results show that all approaches have individual advantages and disadvantages: While SVR has the shortest training times, RF provides the highest quality results - but with relatively high training times. The neural network, on the other hand, performs in a balanced way and provides good results at short training times . In the context of the efficiency discussion for autonomous quality control loops, it must be taken into account that the training of the models in this approach has taken place on the basis of 315 million test data and that a lot of time has gone into the ***database generation***. In many cases, such a good database is not available and if so, a great deal of effort must go into it.

Another important use case of ML approaches for manufacturing processes is the field of additive manufacturing. In their paper on this topic, Meng *et al.* [19] address various use cases for ML in the field of Additive Manufacturing (AM). AM is particularly interesting because the process is highly dependent on various parameters, such as print head speed or layer thickness, as well as batch-dependent material properties. In addition, the change in the aggregate state of the material used and the high process temperatures as well as associated cooling processes complicate the considerations immensely.

Accordingly, data-based approaches that do not require a detailed understanding of the process are particularly well suited [19]. Meng *et al.* [19] highlight that due to poor geometric reproducibility and insufficient surface finish, parts still cannot be used in industries such as aerospace. The freedom of shaping 3-dimensional geometries in AM justify the great interest to get a better grip on the process. Accordingly, various ML approaches, but mostly neural networks, are used when it comes to detecting defects that occur and controlling process parameters depending on the resulting quality. For example, Francis and Bian [20] developed an approach for geometric defect compensation in the L-PBF process using an ML model with convolutional neural networks (CNN). Using the process temperature and some processing parameters as input, the trained ML model can predict the geometry difference, which is then imported into an existing CAD model in the reverse direction to achieve error compensation.

From the analysis of the current state of the art, the following issues arise which are relevant for the elaboration of a more advanced approach for ***Autonomous Quality Control Loops***:

- Database:
  - *How good is the database?*
  - *How can it be built up in an efficient way?*
  - *How can the database be cleaned without bringing in explicit knowledge?*
- Machine Learning Approach
  - *Which approach should be selected*
  - *What ist he variation in result quality for different approaches?*
  - *When does explicit modeling of the process make more sense?*

3. Summary and Outlook

Quality control loops hold great potential for automating quality assurance systems and reacting agilely to negative quality trends as well as supporting the ramp-up-phase in reconfigured production systems. In today's still ubiquitous, heterogeneous and complex data landscape and difficult-to-model, multivariable-dependent processes, implementation is correspondingly complex. Producing companies are therefore deterred from any efforts. The establishment of a standardized data model for quality data to be evaluated and the data-based modeling of complex processes using ML methods counteract this and enable the design of autonomous systems for quality control. The foundation for this is laid in Chapter 2.

In a next step, the findings will be combined to form a holistic approach to autonomous quality control. The goal is to develop a framework that is generic and that enables a process-independent implementation of quality control. The quality data model based on the management shell standard combined with a machine learning algorithm for data-based correlation analysis between process parameters and the resulting quality outcome represent first steps in this direction.

The developed solution has the potential to shorten ramp-up phases in production start-up, to make quality assurance processes more efficient, to minimize rejects and, in the best case, to establish a standard for the provision of quality data.

The approach needs to be validated against a suitable industrial use case. An important part of the analyses will be the comparison to conventional quality control loops, which will focus on the control quality as well as the implementation effort.

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