Using context data to improve the overall product quality in process chains

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Abstract

Process quality has reached a high level on mass production, utilizing well known methods like the DoE. The drawback of the underlying statistical methods is the need for tests under real production conditions, which cause high costs due to the lost output. Research over the last decade let to methods for correcting a process by using in-situ data to correct the process parameters, but still a lot of pre-production is necessary to get this working. This paper presents a new approach in improving the product quality in process chains by using context data – which in part are gathered by using Industry 4.0 devices – to reduce the necessary pre-production.

Keywords: Industry 4.0; IoT; Process Data; Quality Management

1. Introduction and motivation

Process quality has reached a high level on mass production, by utilizing well known methods like the design of experiments (DoE) or Six Sigma. These techniques and methods work well for single process steps, but have the drawback of many required experiments under real production conditions, which cause high costs due to the lost output. Active learning is a modern approach to overcome this drawback. Active learning methods require only a small set of training data for an initial adaption to the process. In the course of production, active learning algorithms continuously refine the monitoring system if required [1]. Other approaches such as Advanced Process Control (APC) or process monitoring systems use process patterns, to offer at least a good/bad decision based on these patterns. Over the last decade the research led to methods for improving a process by using in-situ data to correct the process parameters, but still a lot of pre-production is necessary to get this working. To give an example, for complex injection molding parts, it takes about 1000 units to get such a system working. Another strategy is to test more, which is economical for highly costly parts. In semiconductor industry, for example, run-2-run control is applied in numerous process steps. In lot-2-lot control, the decision and control loop is based on measurement data from only one workpiece in a lot [2].

Technically, these process control methods are implemented in Computer Aided Quality (CAQ) systems that collect, store, analyze and control the quality related process parameters.
Usually these CAQ systems collect process data from more than one process step, but they control the different process steps isolated from each other.

Equally, to this situation more and more information and communication technologies (ICT) are implemented in a factory, ranging from technical process parameters to the whole value adding chain. This massive application of ICT allows to make much more information available than today and enables a finely granular process control on all levels of a factory and over the whole life cycles of products, factories and processes.

Although implementations of DoE and I4.0 concepts have notably increased in the last years, many production chains are not yet covered by these concepts. The reasons for this are complex, some of them are

- the loss of production capacity when tests have to be carried out, as parts produced under these conditions may not be sold under current quality agreements, i.e. they have to be scrapped,
- the complex interaction of the operational software systems, starting with the order control, the production planning and scheduling systems up to the technical process control systems of individual machines and devices.

Therefore, new approaches are required to overcome these challenges in order to improve the knowledge of the critical parameters by considering the complete process chain.

This paper presents an approach for a Meta CAQ system, capable of collecting process data from machines, traditional CAQ systems, MES or PPS system as well as context data. Here, context data are machine IDs and time stamps which allow to bring with low effort the data of the different ICT systems and machines in relation to each other. Based on the collected data and their context assignment, it is possible to monitor process data and their influences on the entire process chain. The approach is prototypically implemented in a process chain with injection molding of two parts, which are assembled and welded together later.

2. Related Work

Statistical and empirical methods for process optimization have proved their effectiveness and applicability in industrial processes. The Design of Experiment (DoE) method was developed in 1935 by R. A. Fisher [3]. In the 1980ies, the method achieved worldwide recognition and became a standardized element of engineering education [4]. The main objective of DoE is to create a robust process by using experiments in the most efficient way [5]. Six Sigma was developed in the middle of the 1980ies by the US-American company Motorola [6] and has become a successful element of quality management. Six Sigma is a powerful method that enables companies to use simple statistical methods to achieve operational excellence [7]. The method is used mainly for designing and production processes. The classical Six Sigma process is structured in a “Define, Measure, Analyze, Improve and Control” (DMAIC) cycle. The Taguchi method is the most widespread method to describe the quality loss in relation to the deviation from the target goal [8,9][8–10]. It is used in particular in the quality control of products and processes [10].

Taguchi introduces a specific loss function, in principal this does not describe, if we are “in-spec” or not, but how good the result is centered in the spec range. This helps to improve the process but also leads to increasing use of resources.

Advanced process monitoring systems utilize techniques like neural networks or fuzzy logic, or even combine them as a “general regression neuro-fuzzy networks” (GRNFN) [11] to get an automated “good/bad” decision without inspection of the produced parts, by analysis of the so-called state vectors which form a kind of fingerprint for each production cycle.

Newer approaches based on the I4.0 paradigm emphasizes the importance of a holistic view on process chains. It comprises the concept of digital twins (review e.g. in [12]) for a digital counterpart of real work pieces in production. Digital twins are an excellent source of data for process control applications (see e.g. [13]). Digital twins can be used on different abstraction layers depending on the track & trace capabilities in the process chain. In current research and technology development, digital twins are mainly used for the representation and tracing of individual work pieces. However, there are many products and corresponding production chains where tracking is a best lot wise or batch wise. Statistical distributions within the batches yet exhibit a high potential for process control and optimization. Work has been done for using digital twins to improve real-time geometry assurance [14]. In their conclusion, the authors suggest to make real-time adjustments batch wise based on digital twin data. All of these methods require a certain amount of time for learning or experimenting, so their use has disadvantages with small lot sizes.

In [15] and [16] the authors present an approach to use IoT devices to reduce this lead time by using inexpensive IoT sensors to collect more process data. For this purpose, they rely on IoT sensor grids, whose data are evaluated using advanced statistical methods.

3. Concept

The key idea of the QP-Mon approach is to enable quality monitoring along the whole process chain with less effort than today. Therefore, process data from different ICT systems such as the CAQ system or the MES are collected together with context data in a database, in a so-called Meta CAQ system. The additionally acquired context data namely the machine ID and time stamps enable a fast data selection for further analysis.

The QP-Mon system links all gathered data to existing data records from the production accompanying information system, for example, process specific CAQ systems and MES or PPS systems (Fig.1). The traditional CAQ system also contains required information about the individual process steps such as the specifications of the semi-finished products and the sequence of process steps. Based on the challenges stated in the introduction the following requirements for the QP-Mon system architecture are derived:

- No extra tests with deviating production parameters shall be made in the production (as required for DoE),
- No hardware and software changes to machines or devices itself shall be made that endanger existing quality standard certifications.
The additional data from the process shall be acquired as non-invasive as possible.

For this purpose, a system approach is developed that is flexible and scalable, so that it can be easily adapted to different process chains. The QP-Mon approach comprises a new ICT system (named QP-Mon system) on process chain level. Key components of the system are a dedicated hardware platform as well as software modules for information pooling and storage, data analysis and visualization as well as user interface (Fig.1).

3.1. Hardware platform and information interfaces

By using modern IoT devices such as sensors and edge devices, which have sufficient computing capacity, it is possible to use proven ICT concepts. In this way, a fully functional network can be set up at low cost, using or influencing the existing infrastructure as little as possible. The principles of a service oriented architecture (SoA) allow a flexible integration and the exchangeability and expandability of functions and modules. As explained in the introduction, the process chain and the corresponding process stations can be in principle unaltered. However, it is possible to integrate additional sensors, if required. Examples for additional sensors are the acquisition of environmental data facilitating quality monitoring. Another example are productions where quality monitoring is improved by process data represented by time series (i.e. by process data that is acquired with a high sample rate). Traditional MES and CAQ systems are often not capable of storing time series of this type for individual work pieces.

For the hardware design low-cost edge devices are used to acquire the additional physical sensor data, which are pushed to the QP-Mon information pool and storage. Moreover, the QP-Mon system has communication interfaces to existing ICT systems along the process chain such as MES / PPS systems and process step specific CAQ systems.

3.2. Information pool and storage

The information pool and storage module of the QP-Mon system stores data from different ICT systems along the process chain. Traditional CAQ systems already contain information about individual process steps, including specifications of semi-finished products and the sequence of process steps, i.e. the flow of the parts. The unevaluated data or states such as production interruptions or process recipes are read directly via the control systems and interfaces of the production machines. Even data that is only available in spreadsheet form can be collected and assigned.

In addition, the QP-Mon system collects and stores additional context data that is not available in the aforementioned ICT systems that is however required for quality monitoring. Context data also e.g. includes machine ID, start and stop time of sub-processes and time stamps that enable a fast data selection for further analysis.

This especially applies to batch productions where it is neither technically required nor cost effective to mark all work pieces individually. In this case, semi-finished work pieces are often stored as bulk material in containers or boxes before they are transferred to the next production machine. ID labels on transport boxes between process steps are a valuable source of information that is stored in the database. In this case, quality data will not be assigned to certain work pieces, but to containers or lots. The QP-Mon system records this assignment (similar to batch management functionality in CAQ systems) as well as the mapping of work pieces to containers or boxes. This approach is sufficient for most of the data which are environment related (temperature, humidity). For other data, like tool temperatures or pressures, this works by using statistical methods.

Fig.1. Concept of the QP-Mon system.
3.3. Data analysis & visualization

The objective of the data analysis module is to detect process anomalies along the process chain with minimum time lag. By indicating them to human operators, the operators can efficiently apply counter measures. Anomaly detection with minimum time lag is also the base for automatic process control, including adaptations of process parameters in subsequent process steps.

From an algorithmic point of view, the detection of anomalies is based on (supervised) machine learning ML algorithms (ML algorithms) that capture correlations between machine and process parameters on the one hand and on quality measurements on the other hand (Fig. 2). This especially includes quality measurements at end-of-line test stations in (linear) production lines.

The ML algorithms predict the outcome of quality measurements at a given process step \( n \), based on all available data from process steps \( 1 \ldots m \), where \( m < n \). The machine learning is supervised, as the results of quality measurements are known for all work pieces that have completed the process chain. ML algorithms that are implemented in the data analysis module are e.g. neural networks, random forest and LSTM. The ML algorithms are trained during normal production and they are already applicable with a reduced number of necessary cycles / production runs. This is realized by a stage approach: In a first step, it is evaluated by a similarity measure if the prediction quality of similar data sets is beyond a given threshold. In this case, in a second step, the quality value (of interest) is actually predicted. By using this approach, the ML algorithms can already be used during ramp up or commissioning when the data set is yet small. The training set for the ML algorithms is continuously increased with data from work pieces that have completely passed the process chain.

3.4. User interface

The individual QP-Mon devices can be configured via a web interface. These are e.g. the data of the current job, the assignment of sensors, current job number or machine assignment.

4. Implementation

The QP-Mon system is implemented as a Linux framework that runs on low-end systems as well as on high-end workstations. Fig. 3 shows a complete implementation based on a Raspberry Pi, which is integrated into an industrial grade switch housing and offers IP65 protection. The QP-Mon systems operate with a Debian based operating system (Raspbian) and support external sensors with both 1-WIRE™ and I²C™ bus. Due to the electromagnetic interference to be expected in the factory environment, the sensor wiring is realized via shielded twisted pair cables. A number of different sensors (temperature, humidity, current, air pressure) were utilized. In particular, up to 20 1-WIRE™ sensors (temperature, pressure, voltage, current) can be connected to two up to 50 m long bus cables, as well as several I²C™ sensors.

The 1-WIRE™ sensors can be added or removed during operation. The corresponding data is automatically collected after connection and transmitted to the QP-Mon information pool and storage.

The implemented QP-Mon system has as a wireless access point function. Thus, it is possible to access the user interface on-site at a machine. This enables an easy configuration of the operating parameters (e.g. machine number, order number, part assignment) for identification in the database and on the labels as well as checking the QP-Mon system operating parameters with a smart phone or tablet. The implemented data acquisition of the QP-Mon system is redundant: In addition to transmission via the network, the data is stored in a local round-robin database, which is able to keep the data of several days of production stored. These data are downloadable via the configuration web interface when connected to the QP-Mon system’s own wireless network. The communication with the CAQ system is realized with a REpresentational State Transfer (REST) interface. The CAQ system executes its measurement and test orders as usual, including the specified regulations using Statistical Process Control (SPC). The data collected by the QP-Mon system is also processed by the CAQ system (as time series) and can thus be assigned to the data already available in the system. In this way it is possible to supplement the fingerprints of the individual process steps with the influences of the environmental parameters and other process.
parameters of the respective production time and thus significantly shorten the learning phase of the process monitoring systems. Process parameters that are considered are e.g. time series for pressure, temperature or melt viscosity in the field of injection molding (see e.g. [17]) or time series for vibration in the field of ultrasonic welding.

By connecting the CAQ system via the RESTful API, it is possible to exchange data bidirectional between the QP-Mon system and the CAQ system. The integration of the machine learning algorithms in the QP-Mon system also eliminates the need to adapt the functionality of the CAQ system, whereby the integration of the QP-Mon system functionality into the CAQ system would of course be possible.

5. Evaluation

The QP-Mon system has been tested in an industrial use case on injection molding machines of plastic parts of an automotive supplier. In the first step, the structure of the QP-Mon system was used to optimize the fit of two injection molded parts, which were ultrasonically welded and then tested for a specific air passage. For this purpose, possible influences on the mean value of the produced parts were investigated and the corresponding data were assigned to the production interval of a transport box (Fig 5). For a more detailed context data acquisition each production order has been assigned to transport boxes by a label. Therefore, in this use case specific implementation of the QP-Mon system a label printer has been integrated. The QP-Mon system produces an adhesive label for each new box at the two molding machines, the operator starts this by pressing a button. The start of a new transport box is also transmitted to the QP-Mon system. So, the gathered data could be related for a certain time slot (the time, this box was filled) for this process step. When the box enters the assembly process step, the QR code of the box is scanned and registered. The code contains the order data (as printed) in JSON or XML format. As a result, the corresponding time periods of the subprocesses can be correlated throughout the entire process flow. (Fig. 6).

The data that is recorded during the production of the injection molded parts (or during the filling of the load carriers, here approx. 20-30 minutes) - in detail, these are the temperatures recorded by the QP-Mon system (ambient, flow and return temperature of the mold temperature control), relative air humidity and pressure are later combined with the

![Fig. 4. Influencing parameters.](image)

![Fig. 5. Relating process data to a timeframe.](image)

![Fig. 6. Evaluation use case.](image)
(offline) information regarding the residual moisture of the granulate (from the dryer control system, MOTAN), the set process parameters such as screw temperature, clamping force, holding time and tool temperature (from the injection molding machine management system, ALS) and the adjustment data of the mold process optimization (Priamus) recorded in the QP-Mon database.

Due to the time stamps available for all these data, these influencing variables, which lead to a shift in the median of the geometric dimensions, can be assigned. This is possible by scanning the adhesive labels of the boxes of the two components of the product during assembly prior to ultrasonic welding and sending them to the QP-Mon system. The data of ultrasonic welding, welding energy and path (Sonotronic) are also assigned through the direct sequence after assembly. The data of the ultrasonic welding process is also added offline, as well as the data of the immediately following pneumatic test. A following pneumatic test (not shown) provides the actual flow rate measured in addition to the good / bad decision. This value can be used as a quality function - the better the two parts fit together, the better the flow rate performs at its target value.

As soon as sufficient data has been collected for a product, more suitable parts can be brought together during assembly by selecting appropriate load carriers. This would allow for an optimization of the tolerances of product components, e.g. in the case of individual parts that cannot be separated again, like ultrasonic welded plastic parts.

The first results showed a good tendency, but for complete statistical validation further and longer time series are required.

6. Conclusion

In this paper we present an approach of an ICT system enabling quality monitoring along the whole process chain with less effort than today. For this purpose, a Meta CAQ system QP-Mon has been designed to collect and analyze process data from different ICT systems together with context data. In order to interrupt the operational processes as less as possible, the concept was prototypically implemented as a stand-alone low-cost version using Raspberry Pis. The evaluation showed that the system approach worked. The idea of making the additional functionalities available for machines and the machine management systems during normal factory operation was accepted and appreciated by the validation company. The analysis of the data acquired so far, shows in a way to get more reliable in-spec decisions. However, for a valid result the approach has to be tested over a longer period in different scenarios. Unfortunately, the experience also showed that this independence has to apply to the normal factory network. Further experiences of the evaluation were that the manual triggering of the generation of the adhesive labels has proven itself, the manual reading of the box labels during assembly has not. A barcode reader has to be installed at the feed of the parts boxes at the assembly station for automatic reading of the labels. An independent communication infrastructure is necessary, and this is being implemented in current follow-up projects. Further research activities focus on simplifying the connectivity to the process data by integrating them into a manufacturing service bus, avoiding the need of adding data offline.

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