

Available online at www.sciencedirect.com

ScienceDirect



Procedia CIRP 57 (2016) 498 - 503

www.elsevier.com/locate/procedia

49th CIRP Conference on Manufacturing Systems (CIRP-CMS 2016)

A Data-Based Approach for Quality Regulation

Quoc Hao Ngo*, Robert H. Schmitt

Laboratory for Machine Tools and Production Engineering of RWTH Aachen University, Steinbachstr. 19, 52074 Aachen, Germany

* Corresponding author. Tel.: +49-241-8020695; fax: +49-241-22193. E-mail address: Q.Ngo@wzl.rwth-aachen.de

Abstract

In the customized production more complex processes are required. Companies are challenged by monitoring these complex processes which compared to mass production show a lower degree of standardization and are therefore characterized by higher instabilities. Quality management has developed various techniques to deal with instabilities such as error analysis and process monitoring, which are implemented successfully in mass production. These techniques are based on the principle of causality and are effective in identifying, monitoring and adjusting the main cause of error in isolated effect chains. Within the customized production the elimination of the main cause of error does not lead to a sustained improvement of production quality since causes of error differ due to varied products to be manufactured. Furthermore, processes in customized production increasingly imply immanent interdependencies. The emergence of quality along the value chain is thus getting more complex and can less be explained by an effect chain using the principle of causality. The data-based quality regulation is therefore developed in order to achieve high quality in complex production. This paper outlines the data-based quality regulation as well as its need for research. Afterwards, an approach based on a virtual production model to validate suitable data mining methods for the data-based quality regulation is provided.

© 2016 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

Peer-review under responsibility of the scientific committee of the 49th CIRP Conference on Manufacturing Systems

Keywords: quality management, quality control, quality regulation, zero-defect manufacturing, quality 4.0, data-driven production

1. Motivation

During the time of mass production which was characterized by low product diversity and large quantities many quality methods for error analysis and process monitoring have arisen [1].

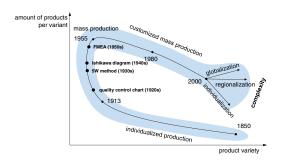


Fig. 1. Times of origin of quality management methods [2]

Although those methods asserted themselves in practice, especially in mass production, they hardly satisfy the requirements of customized production. The main causes of errors during the production processes can still be identified and remedied by using the trusted methods but it does not lead to a persistent improvement of quality. This originates in the different process operations claimed by every individual product. Therefore, the main causes of error differ, depending on the specific product to be manufactured.

Furthermore, different production processes in the customized production expose immanent interdependencies that arise between the individual processes and will continue to increase due to growing product complexity [3]. Owing to the interdependencies between processes the emergence of quality along the value chain is getting less transparent and can only partially be explained or traced by an effect chain. The following example illustrates the influence of interdependencies on product quality:

The process of laser cutting is made up of two parallel running sub-processes. On one hand the laser is guided while on the other hand robots simultaneously move the work piece that has to be cut relatively to the laser. By overlapping these two sub processes the final cutting shape results. However, a previous grind process can change the material property of the work piece as well as influence the result of the process of laser cutting. The interdependence between both sub processes and the grind process cannot be neglected considering the attainment of a high product quality. This example illustrates that due to increasing immanent interdependencies in production processes product quality can only partially be explained by the principle of causality. To explain the emergence of product quality the effect chain has to be extended to an effect network in which causalities of the effect chain remain while interdependencies between the production processes are added, and where the principle of correlation dominates.

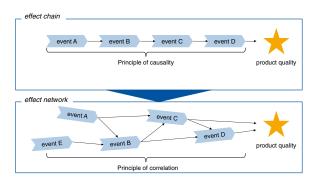


Fig. 2. Extension of the effect chain to effect network

The data-based quality regulation is an approach with the objective to enhance quality in production by controlling correlating production processes integratively. For this, the validation of suitable data mining methods regarding the intended objective is essential. Hence, the research question reads as follows: "How can data mining methods be validated taking account of the objective of data-based quality regulation?"

The state of the art puts emphasis on the potential and relevance of data for optimizing quality in production. The concept of the data-based quality regulation then is outlined with focus on further research needs. Finally, the approach to validate the required data mining methods is provided.

2. State of the art

Subsequently, the emergence of an increasing amount of data in industrial value chains and resulting potentials for quality management are explained. Moreover, existing tools for the processing and storage of huge amounts of data are presented.

2.1. Increasing amount of data along industrial value chains

The increasing amount of data in production provides new potentials for optimizing production quality. The goal-oriented analysis of all available data in production aims at a manufacturing at zero-defects and a learning factory that autonomously adapts to dynamically changing conditions [4]. Industry 4.0 as well as a systematic automatization and digitalization of production go hand in hand. This involves an expansion of sensor and communication networks, an interconnection of production plants through the implementation of cyber-physical systems as well as the assurance of disposability, transparency and security of data [5].

Huge amounts of data change the requirements for data storage. Recent approaches aim at storing and analyzing the data immediately during the process making use of auto-ID technologies such as RFID [6]. The storage of data at the product or specific components is striven. Like this each product or component knows how it has to be processed further. Different kinds of data can be stored directly at the product (figure 3).



Fig. 3. Industry 4.0 aims at data storage in or at products

The storage at the product allows components or products to send crucial signals for process control for themselves [7]. This is not a negligible approach towards greater decentralization in production.

2.2. Increasing product quality through systematic data usage

Along with Industry 4.0 entirely new potentials especially for quality management arise which are discussed in science. Traditional methods such as the quality control chart which are past oriented can be expanded to a real-time quality monitoring [8]. In this context, we talk about a newly to design "Quality 4.0". The objective is the preventive avoidance of errors through the systematic and goal oriented usage of all available data. Quality data are necessary for specification as well as verification of product, process and system compliance. Quality relevant data represent an extension of quality data, as process, product or order data (see figure 3) can describe quality as well [9]. Figure 4 shows exemplary emergence points of quality relevant data along a production process.

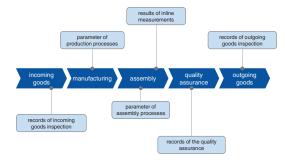


Fig. 4. Exemplary emergence points of quality relevant data

The specific analysis and aggregation of the growing data set yield opportunities to understand the interactions between different production processes and their effect on quality characteristics. Reasons for the poor exchange of quality relevant data and information so far, are a lack of systems and tools to identify and evaluate the data. There is a need for instruments, which allow an aggregation of distributed data and support their evaluation and analysis [10].

2.3. Approaches to generate knowledge from information and data

Current research on the generation of information and knowledge from data is summarized under the term Business Intelligence (BI). The tasks of business intelligence include the qualitative integration. improvement. transformation and the statistical analysis of operational and external data with the objective of generating information and knowledge within a given planning, decision and controlling framework [11]. Müller and Lenz consider business intelligence as the combination of internal and external data in a data warehouse (DW) with OLAP queries for decisionmaking, planning and controlling purposes as well as exploratory data analysis. In order to analyze the collected and stored data evaluation methods, such as statistics, i.e. estimation and testing methods, data mining respectively machine learning are used [12].

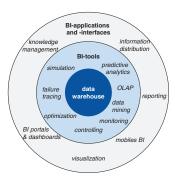


Fig. 5. Business intelligence from a three-layer view

Figure 5 illustrates the tasks of business intelligence by a three-layer view according to Müller and Lenz. The innermost layer acts as a starting point and provides all necessary data. In the second layer, the data processing and analysis take place which use different methods to generate knowledge

from data. The outermost layer includes methods for knowledge and information allocation which convey the generated results from the second layer via appropriate channels according to stakeholder needs [12].

2.4. Interim conclusion

Due to digitalization of production the amount of data generated in production increases permanently. The specific use of these data can support quality management in its functions. In the following, the data-based quality regulation is outlined that extends existing error analyzing and remedying methods of quality management, and also is an attempt towards zero-defect manufacturing.

3. Introduction of the data-based quality regulation

The digitalization of production provides opportunities for quality management to realize innovative methods such as a near real-time quality regulation. In order to illustrate those opportunities in more detail, the motivation and the framework of the data-based quality regulation are presented.

3.1. Application of a digital model in production

The bigger data base allows the development of a model describing the prevailing production state in detail. The model is characterized by real-time capability, since it processes near real-time data, which are either generated by the production processes or have previously been recorded by sensors. By the use of a near real-time model of production, the so called "digital shadow", in combination with data mining methods, the prospective behavior in production can be predicted. Based on the predictions the necessary measures to achieve a demanded state can be derived.

3.2. Framework of data-based quality regulation

The data-based quality regulation rests on quality relevant data. With the aid of quality relevant data, prospective quality progressions of products can be simulated and predicted. Based on these predictions measures can be derived to ensure the quality of all quality relevant production processes.

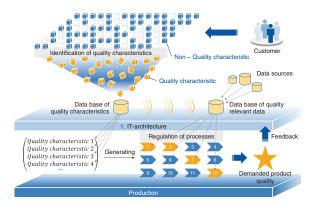


Fig. 6. Framework of data-based quality regulation

The quality relevant data are derived from the quality characteristics, which are determined by the customer. Therefore, the continuous identification of quality characteristics is required so that both the quality characteristics and the derived quality relevant data remain valid. In order to analyze the quality relevant data efficiently, an IT architecture that extracts the quality relevant data from their data sources and manages them in an aggregated form in a quality relevant data base is needed. The quality relevant data base can provide data marts that contain the necessary data for a well-defined field of examination. By analyzing the data marts with the methods of data mining a statement about the current production quality can be made. Irregularities, trends or unusual correlations between different processes are not only evidence of fluctuations in quality, but also represent starting points for the forecast of the prospective quality progression. Based on this forecast preventative measures to regulate quality are derived.

4. Need for research in data-based quality regulation

The need for research is derived from the provided framework and includes four action fields:

- (1)Identification of quality relevant data and data sources
- (2) Development of an IT-architecture
- (3)Application of data mining methods for analyzing and prediction of quality progressions
- (4) Derivation of measures for quality regulation

Subsequently, the contents of the action fields are explained.

4.1. Identification of quality relevant data and data sources

Data-based quality regulation is based on quality relevant data which can be derived from the product's quality characteristics. The presence of a complete, quality relevant data base is key for valid results of the analysis of quality relevant data. For the identification of quality relevant data and their data sources a four step approach is proposed.



Fig. 7. Identifying quality relevant data and data sources

Step 1: Identification of quality characteristics

Data-based quality regulation is used to ensure quality characteristics that are determined by the customer. Identified quality characteristics therefore do not remain the same over time, they are rather changing relative to altering customer requirements. So, in order to achieve high effectiveness in the data-based quality regulation a continuous capturing of quality characteristics is required.

In the area of quality management and market research various methods for the assessment of quality characteristics exist. Examples for these methods are the focus group method, the lead user method or the empathic design. Still a continuous need for research in the optimization of existing methods as well as the development of new methods in this field persists.

Step 2: Identification of quality relevant processes

Due to the increasing product complexity more complex production processes are needed. The quality characteristics are subject to the interactions of multiple production processes that need to be monitored and analyzed collectively in order to ensure a high product quality. Here, the quality relevant processes are focused in particular.

In the second step, the need for research consists of the development of methods to derive the quality-relevant processes from quality characteristics.

Step 3: Identification of quality relevant data

Each quality relevant process is described by quality-relevant data. For example, the manufacturing process laser cutting using a CO2-laser comprises the quality relevant data cutting speed, current intensity or flow rate of the process gas. In conjunction with the data-based quality regulation, the monitoring and regulating of these quality relevant data ensure the quality of the cut surface.

The need for research in the third step contains the development of methods to derive quality relevant data from quality relevant processes.

Step 4: Identification of quality relevant data sources

In this step, the data sources are identified, from which the quality-relevant data are extracted. Possible data sources involve MES or other operating systems that provide the necessary data in the form of spreadsheets, documents, or other media (images, audio, video).

The need for research in the fourth step comprises the development of procedures to identify the quality relevant data sources. Here, the quality relevant data identified in step three serve as reference points.

After passing through the four steps, the quality relevant data and their sources are well known. Next, the configuration of an IT-architecture is required in order to manage the quality relevant data and prepare them for the analysis.

4.2. Development of an IT-architecture

The data-based quality regulation is implemented in the business environment through an IT-architecture that is structured as follows:

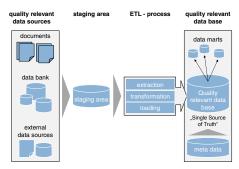


Fig. 8. IT-architecture of the data-based quality regulation

The quality relevant data are extracted from the quality relevant data sources and cached in a workspace calling staging area. Here, the quality relevant data are transformed in order to achieve the required homogeneity, integrity and quality. The storage of quality relevant data is either done centrally in the quality relevant data base, or decentralized along operational process chains in the form of data marts that contain the data needed for specific fields of study. Data marts can be either materialized or virtual. The permanent storage of data marts allows data access in the shortest time. On the other hand, virtual data marts do not need much storage capacity since the demanded data are generated ad-hoc at access using metadata. However, the provision of data through virtual data marts takes a longer time but less storage capacity.

In order to implement the IT architecture of the data-based quality regulation the components of the architecture need to be designed. The design is focus on an adequate period of time for data access and processing.

4.3. Application of data mining methods for analyzing and prediction of quality progressions

According to Müller and Lenz data mining is the semiauthentic uncovering of patterns by the means of data analysis procedures in large and high-dimensional data sets. Data mining is data-driven and hypothesis-free, i.e. it does not require any theories and hypotheses that have to be analyzed statistically. Instead, the hypotheses are generated semiautomatically by data. Furthermore, Müller and Lenz have specified one type of problem, which is particularly suitable for data mining: This problem requires a complex, knowledge-based decision, in which the right decision generates an added value. Additionally, sufficient relevant data to solve the problem are available [12].

The field of data mining provides various methods for different tasks. Among these, the forecast and the association analysis are relevant for data-based quality regulation in particular. The forecast predicts the value of a numeric attribute based on historical data. So, forecasting methods of data mining can be used to predict the quality of products that will be manufactured in the future. The association analysis reveals association rules which describe certain conditions that induce certain events. The following example illustrates

an association rule: "If the cutting speed $(v_{\rm c})$ is 3 m/s and the workpiece has a thickness (d) of 0.1 m, the cut surface is smooth". With the aid of association analysis data scopes, in which the quality relevant data must be located in order to ensure high product quality can be determined. In the case of the presented example data scopes which yield a smooth cut surface might look like this:

Table 1. Exemplary parameter scopes

Process parameters	Parameter area	
	Minimal value	Maximal value
Cutting speed (v _c)	2	4
Thickness of workpiece (d)	0,05	0,2

For the data-based quality regulation, the applicability of data mining methods needs to be validated. It should be investigated whether production quality can be ensured by monitoring, analyzing and regulating quality relevant data.

4.4. Derivation of measures for quality regulation

Using the results of the data mining methods measures that regulate the production quality can be derived. The predictions depict how production quality will behave within a narrow time frame when there are no interventions in production processes. Furthermore, an expected quality progression evoked by specific measures can be predicted. The starting points for selecting suitable measures are given by association rules.

The need for research is to validate the derived measures that regulate the production quality. It should be examined whether the projected quality progressions arrive after the implementation of the measures.

5. Validation of data mining methods

This paper especially focuses on the third action field. In this section a procedure to validate the applicability of data mining methods for the intentions of the data-based quality regulation is provided. This procedure intends the development of a virtual production whose simulation results provide the necessary data for the data mining methods to be validated.

The virtual production has to be both able to represent complexity that is reflected in numerous interdependencies between production processes and capable of generating quantitative simulation results since they are necessary for validation. The methods of System Dynamics which were developed by Jay W. Forrester at the Massachussetts Institute of Technology MIT therefore are predestined for the development of the virtual production, especially due to their focus on modeling complex systems and the opportunity to run quantitative simulations. The usage of flow diagrams allows quantitative simulations of different scenarios over time. A flow diagram consists of stocks which are interlinked with flows. Ultimately, defined entities can remain in stocks

or flow from one stock into another controlled by predefined auxiliary parameters and interdependencies.

The development of a virtual production in form of a production line consisting of a number of production stations is intended. A modular approach thereby is possible. The production processes of particular production stations can be simulated in particular flow diagrams. Afterwards, the particular production stations can be interconnected to a production line.

In the production line as well as in the production station the flowing entities are product characteristics. Each production station is constituted of a stock in which the product characteristic remains during the generating process, various auxiliary parameters which represent specific process parameters as well as cause-effect arrows that establish interdependencies between different process parameters.

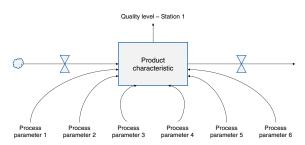


Fig. 9. Virtual production station

Each production station comprises a quality parameter that expresses the quality level of the current product characteristic generated. The quality level is determined by the setup of all process parameters whereby the optimal setup also depends on the product characteristic to be generated.

Multiple production stations can be connected to a production line. In this case, the quality level not only depends on the setup of process parameters from particular production stations but rather from the whole production line. The interdependencies of process parameters across the production line are evoked by additional cause-effect relationships.

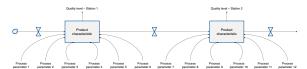


Fig. 10. Virtual production line consisting of two stations

With the aid of the virtual production line the influence of different process parameter setups on production quality can be simulated. The necessary data for the validation of data mining methods thus can be generated. In terms of the objective of the data-based quality regulation the two questions following should be adressed:

- Is it possible to predict the prospective progression of quality by using data mining methods?
- Are data mining methods capable of identifying process parameters whose interdependencies influence the production quality?

The validation through a virtual production ensures a theoretical applicability of data mining methods. However, data mining methods only attain relevance for quality regulation when they are validated in practice.

6. Summary and outlook

The potential of data-based quality regulation for quality management was outlined. Using data-based quality regulation the emergence of quality in complex processes of the customized production can be traced and controlled. For the realization of the data-based quality regulation four action fields were presented, and corresponding research needs were uncovered. Moreover, a procedure based on a virtual production to validate data mining methods was provided. In order to realize the data-based quality regulation in practice further research in the four action fields presented is required.

Acknowledgements

The support of the German National Science Foundation through the funding of the research project "Quality Intelligence (QI)" is gratefully acknowledged.

References

- [1] Geiger W, Kotte W. Handbuch Qualität. Vieweg & Sohn Verlag. Wiesbaden, 2008. p. 482-485
- [2] Bauernhansl T, ten Hompel M, Vogel-Heuser B. Industrie 4.0 in der Produktion, Automatisierung und Logistik. München: Springer Vieweg, 2014. p. 13
- [3] Eversheim W, Schuh G. Integrierte Produkt und Prozessgestaltung. Heidelberg: Springer-Verlag, 2005. p. 172
- [4] Westkämper E, Spath D, Constantinescu C, Lentes J. Digitale Produktion. Heidelberg: Springer Vieweg, 2013. p. 242
- [5] Schuh G, Stich V. Enterprise-Integration, Auf dem Weg zum kollaborativen Unternehmen. Heidelberg: Springer-Vieweg, 2014. p. 73
- [6] Schenk M. Produktion und Logistik mit Zukunft. Heidelberg: Springer-Verlag, 2015. p. 252
- [7] Göhner P. Agentensysteme in der Automatisierungstechnik. Heidelberg: Springer-Verlag, 2013. p. 132
- [8] Dombrowski U, Mielke T. Ganzheitliche Produktionssysteme. Heidelberg: Springer-Verlag, 2015. p. 282-285
- [9] Schmitt R, Pfeifer T. Qualitätsmanagement, Strategien Methoden Techniken. München: Carl Hanser Verlag, 2015. p. 409-416
- [10] Kletti J, Schumacher J. Die perfekte Produktion. Heidelberg: Springer-Verlag, 2014. p. 35-59
- [11] Brijs B. Business analysis for business intelligence. London: CRC Press, 2013. p. 4-6
- [12] Müller R, Lenz H-J. Business Intelligence. Heidelberg: Springer-Verlag, 2013.