Proceedings IRF2018: 6th International Conference Integrity-Reliability-Failure
Lisbon/Portugal 22-26 July 2018. Editors J.F. Silva Gomes and S.A. Meguid
Publ. INEGI/FEUP (2018); ISBN: 978-989-20-8313-1

PAPER REF: 7164

USING "DMAIC" FOR AUTOMATED IDENTIFICATION OF CAUSES AND MEASURES

Patrick Drange[1(*)], Klaus Seiffert[2], Roland Jochem[2]
[1]Fraunhofer IPK, Pascalstr. 8-9, 10587 Berlin, Germany
[2]Chair of Quality Science, Technische Universität Berlin, Straße des 17. Juni 135, 10623 Berlin, Germany
[(*)]*Email:* patrick.drange@ipk.fraunhofer.de

ABSTRACT

In a joined project of TU Berlin and Fraunhofer IPK the initial steps towards a self-optimizing production process have been taken. Data from multiple sensors within the production process are being analyzed to produce an assessment of product quality. With every new input, knowledge about product quality is being generated, as well as archived and applied to optimize future decision-making processes. This results in a self-learning, constantly evolving system.

Keywords: self-optimization, self-learning, industry 4.0, machine learning technologies.

INTRODUCTION

Quality, time and money are essential factors to ensure the competitiveness of businesses. In order to maintain the top position of German industry among the industrialized countries, a work group being instituted by the German government announced the fourth industrial revolution in 2013 (Adolph, 2015). The aim is to increase the rate of innovation, therefore enhancing the development of new processes, technologies and business models. Today, Industry 4.0 is one of the decisive drivers of numerous developments in Germany and beyond (Bauernhansel, 2014), (Roth, 2016).

With the digitalization and networking of production systems, the amount of data available for quality assurance and quality management increased immensely. Assistance systems offer the possibility of intuitive and efficient control of production processes through acquiring, analyzing and evaluating data in real time. In the long term, a fully networked processes chain together with an integrated management system will optimize production machines in real time (Kiem, 2016).

Accordingly, an assistance system named QS-Services has been developed to support the user in understanding process data. Following the Define-Measure-Analyze-Improve-Control Methodology (Jochem, 2015), the application guides the user through the individual steps. By asking more and more specific question, the user interactively characterizes a problem in the define phase. Adding additional parameters, such as tolerance limits have a positive influence on the algorithms and enable more specific recommendations.

RESULTS AND CONCLUSION

It is to be emphasized, that the results of the implementation of measures in QS-Services are documented and stored for further usage, forming the control phase. Therefore, a control loop is implemented, that enables the system to learn continuously and thus derive targeted preventive measures even more precisely.

QS-Services provides a framework to identify causes and derive measures in a transparent way, even without in-depth knowledge in the field of statistical data evaluation. In particular, the analysis of data correlations with regard to product quality is a major challenge. To be able to make statements about the product quality, laboratory tests have been conducted and methods developed in order to derive statements about interaction of process parameters. QS-Services differentiates between the analysis of individual parameters and parameters in correlation to find solutions within increasingly complex production environments.

Due to the findings of QS-Services, it is possibly to intervene directly in the production process. Complaint and error management costs are lowered, and organisations are enabled to further increase their competitiveness through introducing targeted preventive measures to eliminate errors. The assistance system describes a first step towards predictive quality (Hagerty, 2016).

In a sample implementation the assistance system has been integrated in an Industry 4.0 production environment. The Quality Science Lab (Seiffert, 2016) is a production system consisting of independent cyber-physical units. As key technology in Industry 4.0 an off-the-shelf 3D-printer has been equipped with additional sensors and data processing units. Prints of low quality are identified and process parameters are analyzed with the help of QS-Services. Further implementations with industry partners are in preparation.

Presently QS-Services focuses on statistical methods, in next steps machine learning technologies will be implemented. Comparison of this classical and modern approaches will lead to insights about applying data science techniques like cluster analysis and neuronal networks in a production environment. Based on the current research, QS-Services provides a framework to be further developed and to encompass ever more complex scenarios. With the implementation of further technologies and their continuous improvement, the reliable prediction of product quality is possible.

REFERENCES

[1] Adolph, A. *et al.*: Deutsche Normungs-Roadmap, Industry 4.0, v.2, DIN e. V., 2015, p. 8.

[2] Bauernhansl, T. *et al.*: Industrie 4.0 in Produktion, Automatisierung und Logistik, Springer Fachmedien Wiesbaden 2014, p. 9.

[3] Hagerty, J.: 2017 Planning Guide for Data and Analytics, Gartner Inc. 2016, p. 13.

[4] Jochem, R., Herklotz, H., Geers, D., Giebel, M.: Six Sigma leicht gemacht: Ein Lehrbuch mit Musterprojekt für den Praxiserfolg, Symposion Publishing, 2015, p. 24.

[5] Kagermann, H.; Wahlster, W.; Helbig, J.: Deutschlands Zukunft als Produktionsstandort sichern Umsetzungsempfehlungen für das Zukunftsprojekt Industry 4.0 Abschlussbericht des Arbeitskreises Industry 4.0, acatech - Deutsche Akademie der Technikwissenschaften e.V. 2013, p. 1.

[6] Kiem, R.: Qualität 4.0: QM, MES und CAQ in digitalen Geschäftsprozessen der Industrie 4.0, Carl Hanser Verlag GmbH & Co. KG, 2016, pp. 5-6.

[7] Roth, A: Einführung und Umsetzung von Industrie 4.0, Springer-Verlag Berlin Heidelberg 2016, pp. 3-6.

[7] Seiffert, K., *et al.*: Traditionelles neu gedacht: Das Katapult als Lernzeug für die Qualität in der Industrie 4.0, published in Refflinghaus, R; Jochem, R., Kassler Schriftenreihe Qualitätsmanagement, Fachgebiet Qualitäts- und Prozessmanagement an der Universität Kassel 2016, Band 6, pp. 43-59.