Available online at www.sciencedirect.com

ScienceDirect

Procedia Manufacturing 45 (2020) 454–459

Procedia MANUFACTURING

www.elsevier.com/locate/procedia

10th Conference on Learning Factories, CLF2020

A Data-Driven Approach for Quality Analytics of Screwing Processes in a Global Learning Factory

Shun Yang[a,*], Hui Liu[b], Yue Zhang[c], Tobias Arndt[d], Constantin Hofmann[a], Benjamin Häfner[a], Gisela Lanza[a]

[a]*wbk Institute of Production Science, Karlsruhe Insitute of Technology (KIT), Kaiserstr. 12, 76131 Karlsruhe, Germany*
[b]*Bosch Automotive Products(Suzhou) Co., Ltd, Xinglong St. 455, 215000 Suzhou, China*
[c]*Baidu Cloud, Baidu Inc, Shangdi 10th St, 10, 100871 Beijing, China*
[d]*SILU Production Engineering Services Co., Ltd, Yue Liang Wan Lu 10, 215123 Suzhou, China*

Abstract

Quality problems of screwing processes in assembly systems, which are an important issue for operation excellence, needs to be quickly analyzed and solved. A network can be very beneficial for root cause analysis due to different data from various factories. Nevertheless, it is difficult to obtain reliable and consistent data. In this context, this paper aims to develop a method for data-driven oriented quality analytics of screwing processes considering a global production network. Firstly, the overview of data structure is introduced. Further, the data transformation is modelled for edge- and cloud-based analytics across the global production network. Lastly, the rules for analyzing are identified. A joint case study based on Learning Factory Global Production (LF) in Germany and I4.0 Innovation Centre and Artificial Intelligence Innovation Factory (IC&AIIF) in China is used to validate the proposed approach, which is also a new teaching method for quality analysis in the framework of learning factory.

Keywords: learning factory; quality analytics; data-driven; edge and cloud analytics

* Corresponding author. Tel.: +49-152-395-02632; fax: +49-721-608-45005.
E-mail address: shun.yang@kit.edu

2351-9789
10.1016/j.promfg.2020.04.052

1. Introduction

The trend from mass- to customer-oriented production implies an increasing number of variants, shorter product life cycles and higher product complexity [1]. This trend especially affects assembly processes. As one part of assembly processes, the screwing plays an important role in fulfilling the expectations of demanding customers who seek high-quality products at low-cost [2]. Quality problems of screwing processes needs to be quickly analyzed and solved. A production network could be very beneficial for root cause analysis due to different data from various factories. However, a number of challenges exist, including diverse communication standards, proprietary information and automation systems, heterogeneous data structure and poor data quality [3]. There is also a lack of inherent support for industrial devices, making it difficult for manufacturing companies to apply data tools and methods [4]. In this context, this paper is initiated with aim to develop a data-driven approach for quality analytics of screwing processes in a global learning factory. It has been addressed from concept idea to the real set-up and the case study is conducted based on the learning factory global production (LF) in Germany and I4.0 Innovation Centre (IC) and Artificial Intelligence Innovation Factory (AIIF) in China.

2. State of the art

It consists of four aspects in this context, respectively assembly system, quality management, disruptive technologies and data-driven methods.

Regarding assembly systems, various authors present different models for assembly processes and systems to meet the requirements of the customers. A group of students in a Croatian lean learning factory develops the assembly line with implemented Industry 4.0 elements, merging Manufacturing Execution System (MES) and Enterprise Resource Planning (ERP) [5]. An industrial demonstrator is introduced, whose design enables the flexible modification of the assembly information content, the number of connected tools and the number of use cases [6]. A balanced decoupling unit is developed for a safe automated screwing process during Human-Robot-Cooperation [7]. A scalable assembly system is developed based on creating of system configuration [8]. The concept of Evolvable Assembly Systems (EAS) for aerospace manufacturing is introduced, which allows the rapid response to changes during the assembly processes [9].

Many previous studies suggested by researchers for quality analysis include the classification and root cause analysis of quality in order to reduce the number of defects and predict the quality values, thus improving the quality. These researches often use machine-learning algorithms, statistical methods and computer simulations [10]. It exists a strong combination between quality control and quality engineering [11]. A real-time product health status monitoring by means of product specific data entails the effective predictive quality management and exploits the potentials brought by enormous data [12]. A novel technique is indicated for improved Additive Manufacturing predictive modeling to ensure the process optimization and quality control [13]. A machine vision-based quality control system for a learning factory is outperformed [14].

In recent decades, various types of intelligent technologies existed, which have been already put into use in the assembly processes. A methodology based on user interface is explained to achieve better communication during the assembly system [15]. IoT-based platforms [16, 17] and cloud computing [18] are both applied in the research field of assembly systems as well. An IoT-enabled platform ensures more stable information flow, higher visibility and more accurate traceability of real-time information [19]. It is stated that IoT helps to deal with this problem in manufacturing by transforming the traditional systems into modern digitized ones, while enormous economic opportunities are generated at the same time [20]. However, there still exist various challenges by applying cloud computing. Volume, scalability, availability, data integrity, data protection, and data transformation are all important factors, which should be taken into consideration [21]. Therefore, a much more effective cyber-physical system is presented with a new framework and architecture for the manufacturing processes [22].

Numerous data-driven techniques have been developed in the industry domain [23]. As a result, data analytics plays a more and more significant role in quality management [24]. The big data pipeline is introduced so that the devices are able to start joining in the smart manufacturing without extensive technology replacement [25]. Another data-driven and service strategy based on cloud computing is presented in [21] [26], as cloud computing is regarded as a forceful technology to deal with large-scale data. Data Mining (DM) introduced in [27], attracts more attention in recent studies since there is an increasing trend to use DM algorithms for quality improvement.

Despite the growing interest in smart assembly systems and the majority of research exploring issue such as data-driven and quality analytics, it is still lack of concrete method to focus on screw process in global production environment.

3. Methodology

Based on the previously derived research gap, a data-driven approach is developed for quality analytics of screwing processes in global production network. Comprehensive analyses provide complete transparency and real-time notifications for stepping up processes. The deviation and errors can be quickly, easily and reliably detected. This multiplies expert knowledge and facilitates rapid, targeted responses. In a first step, the data structure is created which integrates general parameter and process parameter. Secondly, the data transformation is modelled and finally, data analysis and identification of rules are carried out which can increase the productivity on a sustainable basis.

3.1. Design of Data Structure

The quality of a screw process is determined using a torque versus rotation angle (or time) diagram. The process sub-divided into two distinct phases. Phase one is from the starting point to the time point with dramatic increased slope of torque, more precisely, the defined peak of torque is almost reached. Phase two is the time point which the defined maximum torque is reached to the end of screwing process. With visualized curve for both torque and rotation angle, the violation can be detected, either a certain rotation angle has been reached or an unintentional high torque has occurred, potentially having damaged the screw or the nut thread. In order to ensure the design of efficient data structure, the parameters of screwing process are analyzed and prioritized. First of all, the general parameters are defined such as process name, screwing program, hardware name, location and firmware. Next, the important data for screwing process are selected. For instance, torque, angle, speed, the scope of angle while the torque is reaching the pre-defined peak value. In Table 1, the corresponding description, unit and value type are introduced which enables efficient access and modification.

Table 1. Design of data structure for screwing process.

Parameter	Description	Unit	Value
Torque	Drive torque	N·m	Float
Angle	Rotation angle of screwing process	degree °	Float
Speed	Output drive speed	rpm	Float
The range of angle	The angle of screwing process should be in this scope while the torque is reaching the defined peak value	degree °	Float

3.2. Modelling of Data Transformation

The transformation flow is modelled in Figure 1. The process data is transmitted from tool control to the server in real time, stored in the database. Next, data processing is conducted via minicomputer and the processed data is sent to the Cloud platform through different protocol standard [28]. The web-based user interface, which connects with cloud Platform, visualizes the results.

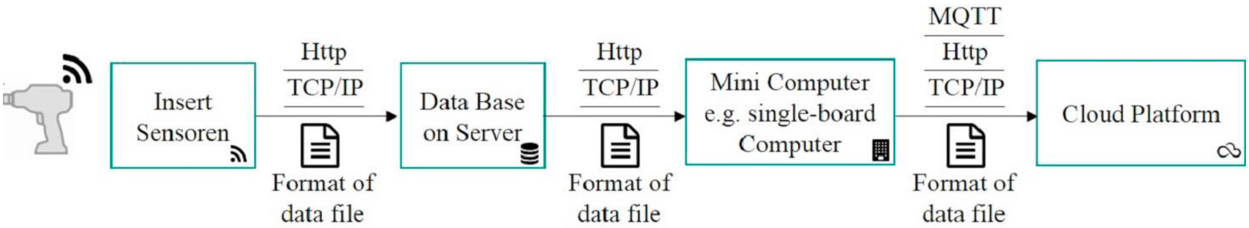

Fig. 1. Model of data transformation from edge device to the cloud.

3.3. Data Analysis and Identification of Rules

A variety of views are available to experts for analysis of the tightening process, so that they can quickly identify process changes early on. In addition to the tightening curve, many other types of assessment are available to enable a systematic analysis of the completed tightening operations and to reveal trends early on. The other assessment types include temperature and humidity. For further data analysis, it is also possible to superimpose multiple tightening curves to compare them more directly in the Cloud platform. The various levels make it possible to quickly and easily navigate through plants, areas, lines, stations, tightening applications, and down to individual channels. A status overview for the entire plant uses color changes to indicate the current status of all connected tightening systems. If defined thresholds in process quality are reached or exceeded, the color changes accordingly. The rules is identified based on Nelson rules in statistical process control [29]. For instance, it shows out of control signals, if six or more points in a row are continually increasing or decreasing. Meanwhile the rules can be also defined that trigger targeted actions such as notifications via logic link. In this way, application of expert knowledge can be multiplied and is also documented.

4. Joint Case Study

A joint case study is conducted in the Learning Factory Global Production (LF) at KIT wbk in Germany and I4.0 Innovation Centre and Artificial Intelligence Innovation Factory (IC&AIIF) at Global Advanced Manufacturing Institute (GAMI, the wbk office in Suzhou) in China. In both locations, the theoretical knowledge on how to use Industry 4.0 for an increased visibility and transparency on the shop-floor is enhanced with hands-on experience. LF assembles the variant motors with nine workstations, two of them are screwing stations. The cordless nutrunners, which have integrated controller with wireless function for data transmission, are installed. IC&AIIF assembles the valve slice for hydraulic control block, which has almost ninety variances, with eight screwing stations in two lines. The handheld nutrunners with integrated measurement transducer are additionally set up in IC&AIIF.

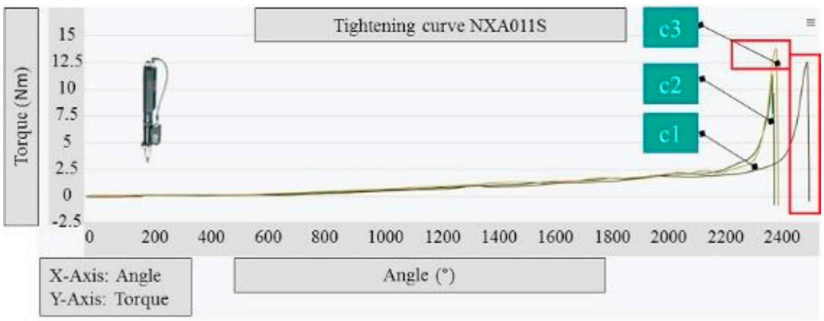

Fig. 2. The data processing and quality issue analysis.

Firstly, the screwing parameters the torque, angle, and the speed of tightening as well as scope of angle are designed for each specific screwing process. For instance, the screwing fastening process for assembly plug of valve is defined to 10 Nm. Secondly screwing parameters are programed into the nutrunners and the configuration of http protocol is conducted, which enables the data transmission from edge device to the server data base. Secondly, the data processing and analytics are executed. In Figure 2 shows the three screwing process c1, c2 and c3 conducted by handheld nutrunners. The pre-defined torque is 10±1 Nm and the scope of angle is between 2200 and 2400 degrees. Although all three screws reach the peak of torque, the angle of c1 is 2600 degree which is exceed the pre-defined scope of angle. The peak torque c3 reached is over the pre-defined torque. The c2 fulfills the pre-defined requirement and shows OK status, c1 and c3 are NOK status. The reason for c1 and c3 could be the raw material issue of screws.

Thirdly, to realize the data-driven quality analysis in global production network, the exchange of screwing data are taken place between both learning factories facilities. The data from data base of local server is gathered through the minicomputer and further uploaded to the Cloud platform via MQTT protocol. In Figure 3 it shows the dashboard via Baidu cloud. The various performance indicators and tolerances as well as envionment status are visualized so that the the problems can be identified and resolved more quickly. The historic data reporting allows continuous process monitoring and documentation of any preventative actions taken. It enables the process security provided by the data manager as an early warning system ensuring quality [29]. The expert knowledge can be also exchanged and multiplied as well as documented. This Cloud platform can be also applied for teaching students for data enabled quality analysis in the framework of learning factory.

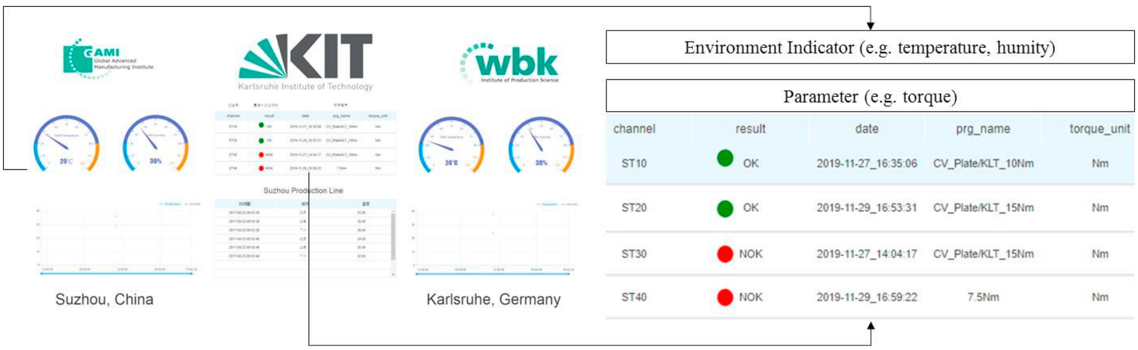

Fig. 3. The data analysis at Baidu Cloud.

5. Conclusion and Outlook

This paper presents an approach on data-driven enabled quality analytics of screwing processes. By considering global production network, the real-time and reliable screwing data is gathered, transmitted and analyzed on Cloud platform. Via the Cloud platform, comprehensive analyses from different locations provide complete transparency and real-time notifications for stepping up processes. Early detection of process risks are realized, especially on faster reaction to screwing process error, twenty percent of analyzing time are reduced based on case study, which leads to reduce failure and reworking costs, results in more output. In future, the further rules for quality prevention and predictive maintenance can be developed and it brings good data basic for self-adoptive system for quality assurance.

Acknowledgements

This research and development project is funded by the German Federal Ministry of Education and Research (BMBF) within the Industry 4.0 Factory Automation Platform – I4TP (funding number 50694) and managed by the Project Management Agency Karlsruhe (PTKA). The author is responsible for the contents of this publication.

References

[1] G. Reisinger, T. Komenda, P. Hold, W. Sihn, A Concept towards Automated Data-Driven Reconfiguration of Digital Assistance Systems, Procedia Manufacturing, 23 (2018) 99–104.
[2] Z. Xu, Y. Dang, P. Munro, Knowledge-driven intelligent quality problem-solving system in the automotive industry, Advanced Engineering Informatics, 38 (2018) 441–457.
[3] A. Kusiak, Smart manufacturing must embrace big data. Nature, 544(7648) (2017) 23–25.
[4] S. Jeschke, C. Brecher, T. Meisen, D. Özdemir, T. Eschert, Industrial internet of things and cyber manufacturing systems, In Industrial Internet of Things, Springer, (2017) 3–19.
[5] I. Veza, N. Gjeldum, M. Mladineo, S. Celar, I. Peko, M. Cotic, Z. Stojkic, Development of Assembly Systems in Lean Learning Factory at the University of Split, Procedia Manufacturing, 9 (2017) 49–56.
[6] C. Z. Li, F. Xue, X. Li, J. Hong, G. Q. Shen, An Internet of Things-enabled BIM platform for on-site assembly services in prefabricated construction, Automation in Construction, 89 (2018) 146–161.
[7] T. Koch, M. Fechter, S. Oberer-Treitz, B. Soltani, Development of a Balanced Decoupling Unit for a Safe Automated Screwing Process during Human-Robot-Cooperation, Procedia CIRP, 72 (2018) 75-80.
[8] T. Stähr, L. Englisch, G. Lanza, Creation of configurations for an assembly system with a scalable level of automation, Procedia CIRP, 76 (2018) 7-12.
[9] C. Shao, Z. Zhang, X. Ye, Y. J. Zhao, H. Sun, Modular Design and Optimization for Intelligent Assembly System, Procedia CIRP, 76 (2018) 67–72.
[10] A. Kim, K. Oh, J. Y. Jung, B. Kim, Imbalanced classification of manufacturing quality conditions using cost-sensitive decision tree ensembles, International Journal of Computer Integrated Manufacturing, 31(8) (2018) 701-717.
[11] F. Mas, J. Ríos, J. L. Menéndez, A. Gómez, A process-oriented approach to modeling the conceptual design of aircraft assembly lines, The International Journal of Advanced Manufacturing Technology, 67(1) (2013) 771–784.
[12] M. Cakmakci, N. M. Durakbasa, M. K. Karasu, G. Bas, U. Gurel, The Importance of Quality Control within the Relationship between the Quality Engineering and Taguchi Methodology, (2015).
[13] Y. Chen, S. Su, Q. Li, H. Yang, Multi-sensor Data Fusion for Online Quality Assurance in Flash Welding, Procedia Manufacturing, 34 (2019) 857–866.
[14] A. R. Mashhadi, W. Cade, S. Behdad, Moving towards Real-time Data-driven Quality Monitoring: A Case Study of Hard Disk Drives, Procedia Manufacturing, 26 (2018) 1107–1115.
[15] L. Louw, M. Droomer, Development of a low cost machine vision based quality control system for a learning factory, Procedia Manufacturing, 31 (2019) 264–269.
[16] C. Sithole, K. Nyembwe, P. Olubambi, Process knowledge for improving quality in sand casting foundries: A literature review, Procedia Manufacturing, 35 (2019) 356–360.
[17] R. Müller, L. Hörauf, C. Speicher, J. Obele, Communication and Knowledge Management Platform for Concurrent Product and Assembly System Development, Procedia Manufacturing, 28 (2019) 107–113.
[18] K. Thramboulidis, D. C. Vachtsevanou, I. Kontou, CPuS-IoT: A cyber-physical microservice and IoT-based framework for manufacturing assembly systems, Annual Reviews in Control, 47 (2019) 237–248.
[19] P. E. C. Johansson, L. Malmsköld, Å. Fast-Berglund, L. Moestam, Enhancing Future Assembly Information Systems – Putting Theory into Practice, Procedia Manufacturing, 17 (2018) 491–498.
[20] D. Mourtzis, E. Vlachou, N. Milas, Industrial Big Data as a Result of IoT Adoption in Manufacturing.,Procedia CIRP, 55 (2016) 290–295.
[21] I. A. T. Hashem, I. Yaqoob, N. B. Anuar, S. Mokhtar, A. Gani, S. Ullah Khan, The rise of "big data" on cloud computing: Review and open research issues, Information Systems, 47 (2015) 98–115.
[22] H. Lee, Framework and development of fault detection classification using IoT device and cloud environment, Journal of Manufacturing Systems, 43 (2017) 257–270.
[23] M. Luo, H. C. Yan, B. Hu, J. H. Zhou, C. K. Pang, A data-driven two-stage maintenance framework for degradation prediction in semiconductor manufacturing industries, Computers & Industrial Engineering, 85 (2015), 414-422.
[24] G. Shao, S. J. Shin, S. Jain, Data analytics using simulation for smart manufacturing, Proceedings of the Winter Simulation Conference 2014, (2014) 2192–2203.
[25] P. O'Donovan, K. Leahy, K. Bruton, D. T. J. O'Sullivan, An industrial big data pipeline for data-driven analytics maintenance applications in large-scale smart manufacturing facilities, Journal of Big Data, 2(1) (2015) 25.
[26] A. Bahga, V. K. Madisetti, Analyzing Massive Machine Maintenance Data in a Computing Cloud, IEEE Transactions on Parallel and Distributed Systems, 23(10) (2012) 1831–1843.
[27] G. Köksal, İ. Batmaz, M. C. Testik, A review of data mining applications for quality improvement in manufacturing industry, Expert Systems with Applications, 38(10) (2011) 13448–13467.
[28] K. Grgić, I. Špeh, I. Heđi, A web-based IoT solution for monitoring data using MQTT protocol, IEEE Smart Systems and Technologies (SST) (2016) 249-253.
[29] T. Zan, Z. Liu, H. Wang, M. Wang, X. Gao, Control chart pattern recognition using the convolutional neural network, Journal of Intelligent Manufacturing, (2019) 1-14.