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Smart Manufacturing with Prescriptive Analytics

A review of the current status and future work

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***Abstract*—Automotive industry faces challenges in manufacturing like increasingly individualized products with a short lead-time to market and higher quality. Additionally to that, new technologies, such as Internet of Things (IoT), big data, data analytics and cloud computing, are changing the production into the next generation of industry. To address these challenges intelligent manufacturing in combination with data analytics plays an important role. In this sense, the integration of prescriptive analytics in manufacturing may help industry to increase productiveness. This paper provides first a comprehensive review of key elements for prescriptive analytics in manufacturing. Furthermore, this paper highlights requirements for a prescriptive analytics based production control, so called prescriptive automation, and finally points out field of activities in this topic.**

Keywords-industry 4.0; smart manufacturing; data analytics; prescriptive analytics; prescriptive automation; internet of things; review

I. INTRODUCTION

Whereas production systems in earlier times consisted of purely mechanical and electrical components, they are nowadays complex systems that combine hardware and software in different ways. Digital processes have an exponentially increased range of functions compared to conventional processes and redefine the traditional process boundaries [1]. Digitized production systems are based on the acquisition, processing and provision of information for machines and objects. The distribution, analysis and target-orientated use of the information offers manifold potentials for an autonomous control of production processes. For that it is important to know what is happening, what will happen and how to react proactively and autonomously. Nevertheless, this proactive control leads to new requirements and can only be achieved on the basis of comprehensive data, so called big data [2] and a change of the architecture for the control and data network in production [3].

Therefore, this paper provides a review about key elements for data analytics, especially prescriptive analytics, on the shop floor. Based on this literature review, this paper identifies requirements for efficient data analytics in manufacturing and a smart production control and highlights fields of action. From this point forward, the paper is structured as follows: Section II, III, IV provide an overview of the state of the art about smart manufacturing, Internet of Things and data analytics, which are key concepts for an autonomous production system based on prescriptive analytics. Section V is a review of key elements and concepts for prescriptive analytics, on the shop floor. Based on this review Section VI provides a recommendation for action for a framework to control production proactively and autonomously based on prescriptive analytics. Finally, Section VII concludes the paper.

II. SMART MANUFACTURING

Smart manufacturing uses advanced sensing-, control-, modelling- and platform technologies with the aim of optimizing production transactions through the full use of advanced information and manufacturing technologies [3]. The visualization of the process performance through the acquisition of huge volumes of real time data is one application [4]. Smart control, as part of smart manufacturing, not only considers the visualization, but also the intelligent control of production facilities that can interact in real time [6]. The goal is to use methods to control and optimize the production process. Depending on which input is available and which output should be controlled, different models for control strategies can be used [7]. Based on the understanding of data analytics, a feedback can be provided to employees or machines, and thus the utilization and production processes can be optimized [5].

A pioneer in smart manufacturing is the IoT. Its devices include sensors, actuators and computers with wireless networks among other things that contribute to automation and monitoring [8]. IoT realizes its potential through the holistic integration of its three components: intelligent devices, intelligent systems and intelligent decisions [9].

III. INTERNET OF THINGS

IoT is defined as "a dynamic global network infrastructure with self-configuring capabilities based on standard and interoperable communication protocols where physical and virtual 'things' have identities, physical attributes, and virtual personalities and use intelligent interfaces, and are seamlessly integrated into the information network" [10].

While IoT applications in the consumer goods market receive a great deal of public attention, the Industrial Internet of Things (IIoT) represents an enormous potential for the

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industry and can cover almost any industrial sector [11]. The IIoT, also known as the Industrial Internet, characterizes the integration and cooperation between machines, analytics and people. The aim is to connect the information processes to make production more intelligent [12]. Therefore, e.g. machines, robots, transport systems, workpieces and control systems must communicate with each other to achieve a higher degree of integration. The enormous amount of data generated by various elements of the intelligent factory allows optimizing manufacturing processes to be more efficient and flexible. Additionally, production costs can be reduced and product quality can be improved [13]. However, to achieve useful information from the enormous amount of data, data analytics can offer a solution.

IV. Data Analytics

Although the development of the IoT has enhanced data collection, the question remains how this data can be properly processed to provide the right information for the right purpose at the right time [9]. Big data analytics become a key base for competitiveness, productivity growth and innovation, because in a big data environment, data sets are much larger and can be too complex for traditional data analytics software. Therefore, it is a challenge to analyze the content of these huge, continuous data streams, and additionally to build more robust and intelligent learning systems [8].

Analytics consists of two main areas: business intelligence (BI) and advanced analytics (AA). With regard to the analysis horizon, a distinction can be made between four levels [14]:

- Descriptive: What happened? (BI)
- Diagnostic: Why did it happen? (BI)
- Predictive: What will happen? (AA)
- Prescriptive: What to do? (AA)

Business intelligence focuses on reporting and queries. Advanced analytics, also called business analytics, goes beyond business intelligence by using sophisticated modelling techniques to predict future events or discover patterns that otherwise cannot be identified. Advanced analytics is about optimizing, correlating and predicting the next best action. Advanced analytics is divided in two parts: predictive and prescriptive analytics [14].

A. *Prescriptive Analytics*

Prescriptive analytics serves to determine a sequence of decisions to obtain a desired result and generally answers the question "What do I have to do to achieve a desired goal?" [15]. This ensures an adaptive, autonomous, time-based and optimal decision and recommends the best approach to achieve specific key performance indicators [16]. Prescriptive systems have two important characteristics.

First, they deliver realizable results in the form of recommendations for action. Secondly, the quality of the recommended activity is reviewed with regard to its correctness [17].

The current literature suggests that prescriptive analytics is divided into three planning levels, at which companies use data-driven decision-making systems. This classification of decision-making follows the analysis by Stein, Meller and Flath [18]:

- Decision making at the enterprise level
- Decision making at departmental level
- Decision making at the individual level

Within the classification of decision making on an individual level, one topic of interest is the intelligent shop floor control with the help of prescriptive analytics [18].

The production control is responsible for the decision process on the shop floor. As mentioned in the previous section, this should optimize the operative work of individual processes. The relevant work in this research field is summarized in the following chapter and we categorized it on five essential categories that are required for prescriptive analytics on shop floor. These include data acquisition, connectivity, data storage, data processing and control. The contributions are listed chronologically within the categories. On the basis of this research work, this article recommends further research for a proactive autonomous control of production processes based on prescriptive analytics.

V. Prescriptive Analytics on Shop Floor

A. *Data Acquisition*

Data acquisition serves as a key factor for intelligent manufacturing, because real time status information is essential for data analytics and production control. The concept of IoT apply the authors to the production area and consider the use of an industrial wireless sensor network (IWSN) for condition monitoring and fault diagnosis of machines [19]. Therefore the article describes the usage of a hybrid framework of fog computing for data pre-processing within the sensors in combination with a cloud computing infrastructure for further data processing [19]. Zhong, Xu,. Klotz and Newman provide a comprehensive overview of IoT-enabled manufacturing [9]. Also an IoT-based architecture for production measurement systems is developed by Hwang, Lee, Park and Chang based on ISA-95 and ISO-22400, which can use data and planning information from MES and ERP systems through interfaces [20]. Giusti, Bevilacqua, Tedeschi and Emmanouilidis further show concrete examples of how IIoT can be used to improve process monitoring and demonstrate a cost-effective retrofit of old machines with IoT devices in an existing production environment [5]. It offers sensor functions and internet connection. The system enables users to capture key process performance metrics and can be alerted of anomalies, as well as remote monitoring via a cloud infrastructure [5].

B. *Connectivity*

Connectivity enables extensive connections and exchanges of knowledge. An architecture with smart gateway and fog-computing is developed by Aazam and Huh, which allows a reduction of the communication load for the core network and more efficient cloud services as well as real time communication for delay-sensitive applications [21]. Wang, Wan, Li and Zhang propose an architecture for a self-organizing IoT network for production control in conjunction with data analytics in the cloud and mobile devices [22]. The approach of Nino, Saenz, Blanco and Illarramendi considers an architecture scheme for data acquisition at field level and data processing with cloud computing in a heterogeneous IT infrastructure, which serves as a case study for an applied research project on error detection using data analytics [23]. The authors extend the possibilities for production control through an architecture based on cloud computing, CPS and IoT [24]. Production control is the focus of Sunny, Liu and Shahriar. The research shows an approach of an agent-adapter architecture for remote control over the internet and the cloud [25].

C. *Data Storage*

An efficient data storage is essential to analyze big data on shop floor. Therefore, the following approach considers storage of the acquired data and describe a scalable service architecture for an analytics system that enables query processing and data analytics of data streams [26]. The service provides uncompressed and correlated data in a warehouse for further analysis. On this occasion, descriptive, predictive and prescriptive analytics tools can be used [26]. From a business point of view the article recognizes that two central prerequisites are necessary for efficient and effective manufacturing processes: process transparency and process responsiveness [27]. The authors address process transparency through a concept for a holistic, production-specific process data warehouse. This integrates operating and process data into a standardized multidimensional warehouse and is based on a generalized meta model of the manufacturing process [27].

D. *Data Processing*

Analysis of the provided data plays an elementary role in decision making on shop floor. Gröger, Schwarz and Niedermann develop an analytics platform for the concept of real time prediction and process optimization. This platform combines relevant data and provides data analytics functionalities. Based on local processing, the approach concentrates on a data warehouse for prescriptive analytics for production control [28].

The research project iPRODICT has the goal to realize predictive and prescriptive analytics and thus to optimize processes. The article analyses the integration of different technologies in order to enable sensor-based decision making in real time for process improvement in the process industry. Within the iPRODICT project, the authors address prescriptive control of processes through event-based process predictions based on big data, with a focus on production planning and control in the context of the process industry [29]. The paper concentrates on the adaptation and optimization of production processes through the proactive analysis of part quality based on sensor data. For this purpose the authors demonstrate a suitable IT architecture which enables the provision of various real time analyses [30]. Additive manufacturing (AM) is one of the most popular applications of data analytics in production [31]. A generic prescriptive analytic method to understand the geometric deformation of products in AM is the topic of Qin, Liu and Grosvenor. The authors develop a service-oriented IoT framework with cloud computing and feedback of recommendations for action to process participants. The framework helps reducing the energy consumption of AM processes [32]. Bassat shows that a digital assistant enables manufacturers to meet stringent requirements in the future and to remain sustainable and competitive. The developed digital assistant enables the analysis of big data collected by IIoT sensors in combination with cloud computing and prescriptive analytics. This supports employees in production in the management of the raw material by specifying the action and thus optimizing the work process and quality [33]. The paper proposes an architectural design and a software framework for the rapid development of prescriptive analytics solutions for dynamic production processes in the automotive industry. The architecture supports the storage of modular, expandable and reusable knowledge bases of process performance models. The decision support system is demonstrated by a prototype to illustrate the principles of the proposed architectural framework [15]. Stein, Meller and Flath consider the development of a sensor-based decision support tool for a manual leak detection process and discusses the development of a prescriptive framework for localizing a leak based on sensor data. The article mentions an integrated framework for prescriptive analytics of manual processes in production environments in form of an analytically supported production system. For this purpose, data is acquired during the production process and machine learning algorithms are applied to train predictive models based on the sensor data. The algorithm creates an individual action prediction [18].

E. *Control*

New technologies such as IoT, big data and cloud-based services are currently changing the field of control technology. Babiceanu and Seker expect advanced production environments to become reality. Therefore the paper proposes modeling guidelines that include IoT connectivity, complex event processing, and big data analytics for operational prediction [2]. The article of Gupta and Chow identifies some of the key research topics related to networked control systems (NCS). These include, for example, network delay compensation and resource allocation. With increasing applications for NCS, real time control is an important issue [34]. The following paper also takes up this topic and separates the physical location of the production control from the production itself. The author recognizes that classical computing is gradually moving into the cloud and offering completely new possibilities in the use of information. Therefore, the approach proposes the implementation of a cloud-based control architecture, the so-called Machine Control as a Service [35]. Coupek, Lechler and Verl connect sequential production and assembly processes via a cloud-based architecture that allows information from a previous production step to be used in one of the subsequent steps for deviation compensation. In this way, the authors recognize that cloud computing offers new possibilities in the use of information and develops a cloud-based control architecture in the production line of rotors. The aim is to generate deviation compensations for subsequent production steps on the basis of collected data [36]. A Control System as a Service (CSaaS) is developed by the authors [37]. It enables the control of a production line in Auckland, New Zealand via the cloud from Stuttgart, Germany by using an NCS. Within the framework, the controller, sensors, actuators and other system components exchange information via a common network. However, it turned out that CSaaS between New Zealand and Germany is not possible due to network challenges, so the controller should be closer to the machine [37]. Steiner and Poledna conclude that the IIoT softens the rigid layers of the automation pyramid by introducing fog computing as an architectural measure for linking IIoT and process automation [38]. According to Patel, Ali and Sheth, fog computing offers production control advantages over cloud computing, but it cannot replace cloud computing because many applications require both fog localization and cloud globalization, particularly for analytics and big data. For this reason the approach proposes a parallel use of fog and cloud computing [39]. Barton, Maturana and Tilbury recognize that manufacturing systems should close the loop and transform IoT data into production knowledge. The authors develop a bidirectional framework for a closed loop from sensor data to machine control to compare simulation and operating data to optimize control approaches [40].

VI. Recommendation for Further Research

The following research topics are the result of the five relevant categories for prescriptive analytics on shop floor as defined in Section V. Production control usually follows a fixed logic, with conditional consideration of dependencies and correlations based on a usually outdated data basis [41]. Digitalization opens new ways to improve decision making through up-to-date and comprehensive data. Table I shows an overview of the authors regarding relevant scientific contributions for prescriptive analytics on the shop floor. However, it only lists papers dealing with connectivity, control and data processing (see Section V). As the review and Table I show, process data extraction for data analytics is often considered, but analysis and optimization takes place ex post the production process in the form of a decision support system. However, the support system still requires a human being as the top decision maker and manual executive element. Therefore, some authors mentioned the idea for prescriptive analytics on the shop floor with an automated closed-loop, but they do not conceptually develop and implement it.

As a result, a research gap is an autonomous, proactive control of the production process by optimizing process parameters by prescriptive analytics during execution, so called prescriptive automation. A key part of this gap is to develop an integrated framework for prescriptive automation. This framework allows to control the process ex ante based on a prescriptive analytics model and autonomous without a human as a manual executive. This framework has to be interoperable with the heterogeneity of communication networks and changes in IIoT for a wide data acquisition on the shop floor. Due to the fact that a huge amount of data is generated, scalable computational power is needed to execute the prescriptive analytics model. This model controls the operational process autonomously. Based on the continuously grown database, the framework has to offer the possibility to update and train the prescriptive analytics model. Finally, this updated model has to be deployed by the framework to the controlling system.

TABLE I. Overview of Relevant Scientific Contributions for Prescriptive Analytics on Shop Floor

	Hybrid cloud – fog computing	***Cloud computing based control***	***Fog computing based control***	***Prescriptive analytics on shop floor with manual closed loop***	***Prescriptive analytics on shop floor with automated closed loop***
[2]	○	◔	○	◔	◔
[6]	○	◑	○	○	◔
[15]	○	○	○	●	○
[18]	○	○	○	◕	○
[19]	◕	○	◕	○	○
[28]	○	○	○	◕	◔
[29]	○	○	○	◕	◔
[30]	○	○	○	◕	◔
[31]	○	○	○	◑	◔
[32]	○	○	○	◑	◔
[33]	○	○	○	●	○
[35]	○	◑	○	○	○
[36]	○	◕	○	○	○
[37]	○	◕	○	○	○
[39]	◑	○	◑	◔	◔
[40]	◑	◔	○	◑	◔
Table legend:	○ not considered	◔ idea considered	◑ concept considered	◕ concept developed	● concept implemented

VII. Conclusion

This paper deals with the change from a purely mechanical and electrical to a data-driven and data analytics-supported production. The paper focuses on the special case of prescriptive analytics on shop floor. Based on the scientific literature, five categories for prescriptive analytics on shop floor with automated closed loop are determined. A comprehensive review of the scientific contributions in these categories is given. As the review shows the idea for a prescriptive automation is suggested, but not conceptually developed and implemented. To address this, a framework which has the in Section VI considered features have to be developed.

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