Real-time Analytics through Industrial Internet of Things: Lessons Learned from Data-driven Industry

Completed Research

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Abstract

Industrial Internet of Things (IIoT) and the increasing role of real-time analytics (RTA) data are currently transforming industry and shop floor work. Manufacturing industry needs to adapt accordingly and implement systems solutions for rich data analysis to achieve increased business value. However, a data-driven implementation of RTA applications, often launched as "Plug&Play" solutions, often lacks both insights into shop floor work and the alignment to user perspectives. This paper focuses both on the technical implementation and the deployment of RTA applications from a design-in-use perspective and therefore we argue for congruence between a data-driven and a user-driven approach. The main findings reveal how configuration and implementation of RTA applications interplay with users' work operations that further extends current IIoT layered models by aligning architectural levels with user and business levels. The main contribution is presented as lessons learned to inform sustainable and innovative implementation for increased business value for data-driven industry.

Keywords: *Industrial internet of things, IIoT, Layered-modular architecture, Real time analytics, Data-driven industry.*

Introduction

Today, digital transformation is on the agenda for all types of organizations, with a promise of increased proficiency in businesses, more effective production and future competitiveness through utilizing data to a larger extent (Andriole, 2017). This is especially true in manufacturing industry. New digital solutions, such as industrial internet of things (IIoT) and data analytics systems are in various ways disrupting earlier technological structures with an increased amount of incoming data (Chen, Chiang, & Storey, 2012; Gilchrist, 2016; Itabashi-Campbell et al., 2013; Tripathi, 2019). Together, these changes create leaps that are rather unique in industrial contexts. Industry 4.0 and digital manufacturing through IIoT has accelerated in interest and has become one of the most hyped concepts embedded in the industrial revolution (Gilchrist, 2016; Lasi et al., 2014; McAfee et al., 2012). IIoT technologies and analytics applications are promised to analyze real-time data for data-driven effective operations and production while assisting everyday decision-making. Consequently, these changes have the potential to drastically improve business performance and business value (Brynjolfsson & McAfee, 2014; Brynjolfsson & Mitchell, 2017; McAfee et al., 2012). Moreover, IIoT probes transformations on all levels within the manufacturing industry, initiating changes in which data-driven business capacity and values are seen as the main drivers to reach effective production (De Carolis et al., 2017). These promises remain to large extend unverified and there are gaps in the literature regarding: i) suitable IIoT analytics network design as too much focus has been put on the sensing architectures for industry networks (Al-Fuqaha, 2015; Verma et al., 2017), and additionally ii) the lack of user-studies aligning IIoT and analytics systems to make sense of data and derive knowledge (Abbasi, Sarker, & Chiang, 2016; Williams, Hardy, & Nitschke, 2019). In order to make sense of real-time analytics (RTA) applications that generate massive IIoT data, we argue for the need to integrate data-driven analytics with a user-driven approach, in line with (Trinks & Felden, 2017; Williams et al., 2019). In this paper, we pursue RTA following Verma et al. (2017, p.1460) definition,"…as the analysis of every segment of the massive IoT data at the right moment in order to obtain business value and drive intelligent decisions."

The velocity, volume, veracity and variety of data used for data-driven values and capabilities are illustrated in exponential growth and the in-coming data is often messy, somewhat unstructured and thereby hard to comprehend by humans (Verma et al., 2017). Due to the aforementioned exponential growth of data, questions related to the usefulness of data, and how RTA applications are introduced, designed, configured and implemented remain unanswered (Verma et al., 2017). It is not enough to collect and process vast amounts of data as the volume will not automatically lead to better work floor routines and further precise actions in organizations (Davenport, 2018; Iftikhar et al., 2019). Instead, there are practice-based gaps in how to collect specific sets of data that can be visualized and used for work practice that rely on real-time analytics data (Davenport, 2018; Trinks et al., 2017). Additionally, there is scare knowledge of how to utilize real-time analytics data on various organizational levels including shop floor practices (Iftikhar et al., 2019). Hence, the understanding of real-time analytics is still in its infancy and there is a need for further in-depth analysis of how RTA can be used in real-world settings in order to achieve business value and support shop-floor production work. In practice, handling the data and knowing how to effectively use RTA for data-driven industry, triggers concern of usability at the shop floor. Especially, when software suppliers state that their RTA applications can be set up as "Plug&Play" software packages, where accessories and services offer instant connection, and the machine will recognize the accessory and automatically generate the correct configurations.

The empirical findings presented in this paper are derived from a design ethnography of introducing an RTA "Plug&Play" application in a manufacturing company in Sweden. From this setting, we describe how the implementation of real-time analytics of data is played out in practical terms. The personnel in our case consist mainly of the shop floor operators and machine engineer technicians. As we wanted to capture the on-going process of design-in-use through the design ethnography, the main contribution is illustrated through lessons learned which include efforts of furthering the knowledge on design; both in terms of the system as well as of the work organization. This is described from an inside-out deployment process of how a new advanced real-time analytics application is configured and implemented. By a design-in-use strategy we refer to the overlap of design and use, in which the design and use phases merges (Islind & Lundh Snis, 2017).

More specifically, we investigate the design-in-use through two research questions: i) How can IIoT layered architectures be aligned with user and business values in industrial manufacturing? and ii) How does implementation of RTA applications influence shop floor operations in manufacturing industry? A general Industrial Internet of Thing (IIoT) model by Al-Fuqaha (2015) is adapted and applied to structure and develop our findings. This layered model is further developed throughout our discussion that is summarized with three key lessons learned: i) Selecting architecture; ii) Harmonizing data structures; and iii) Aligning business and user values. These lessons learned can be expanded by others who want to embark on similar RTA initiatives. By entering the deployment phase with a design-in-use strategy, we suggest that our findings can form a basis to explore new avenues for organizations to achieve more from RTA investments and thereby gain business value for a data-driven industry.

Theoretical framing

Industrial Internet of Things

Internet of things (IoT) is developing as a key technology type within the era of Industry 4.0 (Al-Fuqaha, 2015; Albishi et al., 2017; Boyes et al., 2018; Gilchrist, 2016; Rose, Eldridge, & Chapin, 2015; Trinks et al., 2017; Tripathi, 2019; Verma et al., 2017). The term IoT originated from a British pioneer, Kevin Ashton in 1999 (Rose et al., 2015), and was described as a type of system in which objects in the physical world could be connected to the Internet by sensors. The essential foundation is based on smart sensors that collaborate directly without human involvement to deliver a new class of applications (Al-Fuqaha, 2015). IoT technologies should be built on sensors with self-awareness that will predict their remaining useful life and to automatically produce data from machine sensors through their controllers with functions such as; self-awareness, self-prediction and self-comparison (Gilchrist, 2016). Consequently, Industrial IoT (IIoT) has become a key technology in the frame of forwarding Industry 4.0 (Schuh et al., 2017). IIoT connects other features within the industrial technological landscape, based on the same idea as IoT. IIoT thereby outlines a technology type built of interrelated computing devices, mechanical and digital machines that rely on data and communication between a network of physical objects that feature an IP (Internet Protocol) address for internet connectivity and Internet-enabled devices and systems in industrial settings (Verma et al., 2017). Hence, IIoT focuses on increased visibility and insights into production operations with systems that integrate machine sensors, middleware and software with backend cloud storage (Gilchrist, 2016). IIoT systems generate huge amounts of data, which can be a problem, and methods to handle the large amount and transform business operational processes to gain feedback of results from interrogating large data sets through advanced analytics are needed (Abbasi et al., 2016; Boyes et al., 2018; Gilchrist, 2016). An interest in this paper is to further illuminate IIoT, i.e., the impact of the implementation process of IIoT systems, and to shed light on how massive data is generated and analyzed, as well as illustrate the effect on shop floor work. We therefore adopt to Boyes et al. (2018, p.3) definition of IIoT: "A system comprising networked smart objects,… which enable real-time, intelligent, and autonomous access, collection, analysis, communications, and exchange of process, product and/or service information, within the industrial environment, to optimize overall production value."

Real-Time Analytics

IIoT technologies creates massive amounts of data that in the long-term aim to generate business value through analytics applications. In an early MISQ special issue, Chen et al. (2012) outline business intelligence (BI) and analytics (A) and describe three generations of BI&A; 1) data management and warehousing (1970-1990), 2) web intelligence and analytics (2000), and 3) mobile and sensor-based IoT (2010). With the 3rd generation they recommend to further research analytics and context-aware techniques for collecting, analyzing, and visualizing large-scale sensor data, to ensure business value. Another related stream of research of IIoT analytics technologies (Davenport, 2018) has shown that problems occurred when large amounts of unnecessary data were processed which later proved both time-consuming and irrelevant for decision-making purposes. In realm of the development, (Davenport, 2018) outlines "analytics" through four generations of transformations to reach for analytical capabilities and artificial intelligence, and generate business value: 1) statistic and descriptive analytics, 2) big data analytics, 3) industrialized analytics (predictive and prescriptive), and 4) artificial intelligence (analytics embedded and automated). Given these two streams of interrelated research, this paper is placed after the 3rd era of BI&A (Chen et al., 2012), with specific interest on the level of mobile and sensor-based applications. Additionally, with a focus on real-time analytics applications of predictive maintenance the interest is placed between 3rd and 4th generation of analytics (Davenport, 2018). Analytics describes the theory of analysis and is used to group all existing analytical methods herein. As argued, analytics need to be used in combination with other technological terms to clarify the application scenarios (Trinks et al., 2017). Today, standardized applications for RTA are promising, both in regard to prescriptive and predictive analytics (Verma et al., 2017). These applications allow machine data to alarm when it is time to repair and upgrade failed components, i.e., tracking deviations and measuring statistics for machine capability and quality.

When organizations are designing and implementing RTA technologies built on an IIoT architecture, there are models that illustrate how enabling technologies such as RFID (Radio Frequency Identification), smart sensors and RTA applications and services are linked together. In relation to that, Al-Fuqaha (2015) describe five layers of IoT: i) the object layer, ii) object-abstraction layer, iii) service management layer, iv) application layer, and v) business layers. Together, these are the most essential layers for a robust computing-layered network (Al-Fuqaha, 2015). The object layer collects large-scale sensor data from physical things (e.g., machines) and handles data communication. The service management- and application layers focus on software configurations. These include new types of data-heavy software that collect data, transfer data into applications, and furthers the data into a business layer, making the data applicable (Al-Fuqaha, 2005). Yoo et al. (2010) discuss layered-modular architecture from an IS perspective. The view presented therein, is based on a platform architecture, in which there are four layers: i) a content layer, ii) a service layer, iii) a network layer and, iv) a device layer. While we acknowledge the importance of separating the layers, as described in Al-Fuqaha (2015), neither the model from Al-Fuqaha (2015) nor from Yoo (2010) fit our case seamlessly. For the purpose of this paper, we therefore densify the model presented by Al-Fuqaha and seek inspiration from Yoo (2010). We focus the analysis on three layers which are of particular interest for the case, by clustering the object and object-abstraction layer presented by Al-Fuqaha (layers i and ii) and by clustering the service management layer and the application layer (layers iii and iv). Figure 1, illustrate the three-layered model used for the analysis of the case, as follows: i) object and object-abstraction layer, ii) service management- and application layer, and iii) business layer.

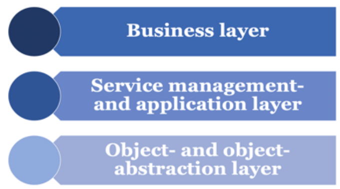

Figure 1. A three-layered model for RTA implementation, adapted from Al-Fuqaha (2015) and further inspired by Yoo (2010)

Research approach

There is a withstanding tradition of ethnography for design and its discount derivatives (Anderson, 1994; Beyer & Holtzblatt, 1999; Dourish, 2006). The difference between ethnography and design ethnography is that in the latter, the designer also actively engages in orchestrating change (Baskerville & Myers, 2015), an aspect which is similar to action research. The aim of the design ethnography approach is to contribute with a shared design experience and to facilitate learning about social, cultural practices and values, built on empirically driven research of real-world contexts. The research approach emphasizes researchers to actively engage with on-going practice towards future-oriented objectives of: "designing, creating, innovating, and improvising artefacts" that may affect the cultural and social setting (Baskerville et al., 2015). Furthermore, it allows for understanding how design activities contribute to and interconnect both work and design ideas sprung from practitioners and designers in iterations close to the empirical setting. Hence design-in-use, actively includes real users within the studied setting. This research case applies design-in-use to the studies of configuration, implementation and use of the RTA application X-top in an industrial shop floor setting. Hence, the case provides in-depth insights into practical real-time implementation process of IIoT system.

While studying design-in-use, various data collection and design activities are possible, such as observations, interviews, informal meetings, documentation, and tests of the standardized RTA application, further on called X-top. We wanted to understand the implementation process of an RTA standardized application, what type of data that ought to be included, how to use the generated data, and to understand the correlation to the ERP system and quality of statistics to support everyday practice. A design-in-use perspective has been applied in our study, and iterates around a design-in-use cycle that exchanges outputs from use as inputs to design or re-design of an RTA application from a real-world problem (Islind & Lundh Snis, 2018). Through studying design-in-use we present an illustrative account of the design, introduction and use that are derived from in-depth observations and inquiries of what personnel experience during the studied process. In this case, the first author actively engaged in the introduction of the RTA application, while doing observations and step-by-step inquiries.

Data collection and Analysis

The data collection included several types of research activities, see Table 1. Besides continuous formalized observations of the operator on the shop floor, interviews and focus group sessions were conducted. The data gathering also included participation in meetings, workshops, oral presentations with feedback loops as well as formal and informal discussions.

Date (m/y)	**Respondents (#)**	**Activities**	**Duration**
Dec -18, Oct 19 & May -20	Operators (7)	Observations and interview on shop floor work	2 obs, 6 hours 1 interview, 1 hour
May -19	Production leaders (3)	Observations and interviews, shop floor	4 hours
Dec -18	Project manager (1)	Interview about the planning and scheduling in the ERP system	1 hour
Feb -19	Machine Engineers (5)	Focus group interview	1,5 hours
Feb -19 & Oct -19	Supply manager X-top (1)	Interview and meeting about installation status and functionality	1,5 hours
Apr -19	Management group (5)	Presentation and discussion of X-top configuration and implementation	1 hour
From Dec –18 – May -20	ME manager	Development and follow up meeting of X-top configuration, implementation, and use	15 meetings 1-3 hours each

Table 1. Overview of data collection activities

These activities were targeting towards a deeper understanding of the actual configuration and implementation, and what interventions took place in practice (Baskerville et al., 2015). The research lasted 1,5 years in close collaboration with staffs in a manufacturing company. All together comprising about 20 different respondents: operators, project managers, Machine Engineer (ME) technicians, ME manager and the management group. All respondents signed an informed consent form for the data collection activities. The observations were partly video recorded and summarized in field notes. The interviews and focus group sessions were conducted through thematic interview guides targeting the various respondent groups. All sessions were audio recorded and verbatim transcribed into text. The interview sessions covered topics related to benefits and problems while using old (e.g., CAD, PLM, SAP) and new applications, and how to interpret and make use of massive real-time data. Throughout the interviews, a conversational tone and open-minded approach guided the interest to understand the respondents views (Tanggaard, 2007). We were aware of the power dynamics during the interviews (Myers & Newman, 2007), and especially questions about the company and the respondents' experiences of sensitive information, see Table 1. The analysis was conducted through qualitative content analysis in order to interpret the empirical data as an inductive approach (Bryman, 2012; Kohlbacher, 2006). We used the qualitative data analysis software (SQDAS) NVivo 11th edition for transcriptions and coding of the content analysis. The design-in-use perspective was applied as an iterative process of three interrelated processes that were ongoing simultaneously (Islind et al., 2018; Islind & Snis, 2017). Also, during the content analysis, the intertwined character of design-in-use was viewed as an abductive process of deriving concepts from theory, as an foundation for the lessons learned and to reach for a theoretical understanding (Bryman, 2012).

Empirical setting: Siemens Energy

The research setting is a local manufacturing plant in West Sweden, and part of the global Siemens Energy (SE) company. The local SE with approx. 150 employees is manufacturing combustion chambers which delivers to the head company manufacturing “state of the art” full industrial turbomachinery. Due to the heavy products and the high-quality product demands, the production cycles are up to one year. Production at the local Swedish sites is arranged in functional production units with low automation grade and irregular production flows. Some operations rely heavily on manual work such as welding, conducted by experienced operators and technicians. Cutting and welding in stainless steel is performed with machines for laser welding, pressing, and forming. At the local SE, the standardized RTA application X-top was installed on a fiber-laser machine. This high-capacity laser machine needs to run through many product variants and batches and has an inbuilt automation system with PLC (programmable logic controller), that needs full surveillance by one operator, during two daily shifts. The X-top system is developed on the principles of real-time IIoT and collects data generated from sensors, devices, and automated signals of the laser machine. It was launched as a “Plug&Play” system aiming to connect machines with turn-key wireless data collection, and web visualizations for various end-users, especially targeting operator work. X-top is designed for detecting deviations and disturbances, however specific local configurations targeting customer adjustments, needs to be done. X-top manages a range of real-time deviation support on signals for measuring the machine health: production overviews (scheduled and running status), disturbance overviews, charts, and statistics. It complements the ERP-systems (SAP) production and resource planning. It this means that the real-time data from X-top complements and is measured against the SAP planned production data, but does not replace it, rather interlinks plans with factual actions.

Findings

Problems at the shop floor

One problem is the large amount of production deviations due to stops in the production which generates high costs. The local company is not sure when or why deviations occur, neither on daily basis nor during the year cycle. On daily basis, operators and technicians start their operations given from the production order, generated from SAP, including information of production time: both machine time and manual operations. When finishing, they stamp the whole working cycle. They also must rely on product drawings and CAD instructions that are stored in a PLM system integrated in the SAP suit, of which they initiate and finish the operations. Production planning orders and drawings are available in both the SAP and the PLM system as well as on paper. As their work routines now are more digitalized and followed up in real practice by the X-top system, they need even more to communicate both men to men and on written notes in and between shifts. Hence, operators and technicians get stressed of running machines, handling manual work, and updating both digital and manual data. The variations of outcome for running a machine effectively, becomes related to individual performances and operators' specific competences, rather than on a high qualitative and general work process level. A way of tackling these problems, the company decided to test a new application for real-time analytics, X-top, with a pilot-implementation on the fiber-laser machine. A potential to control and optimize production, through interpretation of interconnected machine data that appeared to be an essential goal for the operators and the manufacturing engineers' technicians (MEs).

Problems with the system configuration and implementation

The following description of the configuration and implementation of X-top on the fiber-laser shows the steps that the company had to handle, to achieve an up-running functionality for real-time analytics of data. Even if X-top is claimed to be a "Plug&Play" application, there were problems during the configuration and implementation phases. Other complications regarded integration of the production order data (defined by the MEs and imported from SAP) in combination with the real-time machine data. This whole phase, from configuration to implementation took about 10 months to get the system running, 9 months longer than estimated. In spring 2020 X-top was fully installed on the fiber-laser and generated real-time machine data.

Implementation on the object- and object-abstraction layer: The object abstraction layer represents the physical sensors from the IoT, for data collection and process information. Configuration work regarded to find appropriate sensors signals and tuning the data communication etc. Actions taken were: i) time measuring of data: An external electrician firm together with internal technicians installed smart radio loggers on selected sensor signals on the fiber laser with RFID (Radio-Frequency Identification-Data) technology and ii) data communication/internet: By using RS-485, a multipoint communications standard (an alternative to Wi-Fi), electrical signaling is balancing and defining the electrical characteristics of drivers and receivers for use in serial communications systems. Above this network, there is a mesh network, with nodes connecting directly, dynamically, and non-hierarchically to other nodes in the data communication topology. During this phase, many iterations occurred, and it took approx. 3 months to proceed (way over time plan). In addition, external IT support was needed, even if the X-top supplier was continuously supportive.

Implementation on the service management- and application layer: This layer request pairing with specific hardware platform and machine automation. It also concerns the services requested by users on the application layer. Hence, further configurations of the X-top application were to correlate the company-specific production data of production cycle time from SAP. The planned production time is pre-estimated time and includes cycle time + setup time. Hence, data is transferred in real-time to a Microsoft Azure cloud center. Even if X-top only measure cycle times in the running machine, there is a need to measure it against data from SAP against X-top. The following configurations were made: i) import of data: Production data with only cycle times was imported from the ERP system into X-top and ii) definitions of deviation codes: generation of a stop coding list for manufacturing deviations such as machine errors, non-planned production, cleaning, calibration, meeting etc. specific for the company.

Implementation on the business layer: Configurations on this level concerned how to assess and define the measurements from the X-top application, hence, analyzing machine data into business models, graphs, flowcharts, etc. and to support with statistics for daily manual operations. In practice this meant to assess and estimate generated statistics and the aggregated statistics regarding machines running and the deviations over time to make both short (daily by operator) and long-term decisions. Additional system-integration activities to consider during configuration is if new types of real-time data analytics interfere or is strengthening integration to other systems/applications and correlated data, i.e., connecting data from other systems such as SAP, other planning applications and drawing/planning systems. The infrastructure of systems are too many extents very large and over-lapping. From a user perspective X-top use there is a need to change work routines for both operators, technicians and production managers which disrupt but also enhance visualizations and communication of production status.

System Implementation Challenges on Shop Floor Operations

The main operator Rolle runs the fiber-laser machine, with support of the ME manager Kalle. Both were involved in the configuration and implementation of the X-top system during 2019-2020. In March 2020, the system was up and running on the fiber-laser and an installation plan for a Robot and a 3D-laser was developing. The implementation phase was extensive and took 10 months instead of 9 months. Obstacles were lack of specific expertise such as IT support, electricians with data communication skills, and a lack of specification on data communication requirements from the X-top supplier. Even if both Rolle and Kalle were skilled with high IT competence and practical production systems experience, they were stuck without this support. Additionally, the whole system deployment process was not initiated from a management perspective, rather built from a bottom-up perspective and low-prioritized. Even if X-top was a totally new type of system for measuring connected machines, the staff were relieved to find a way to meet the requirements from the global company of increased productivity, through gathering real-time data from every-day operations. Productivity is traditionally measured by calculating hours spent on each product unit, built on scheduled and planned production data from the business system SAP. However, such plans tend to oversee employees manual time spent for handling production units and operations between unit batches, i.e., manual operator work is not measured and planned. Hence, a variety of challenges occurred in the implementation process of X-top, of obtaining effective data and tuning the measurements.

To understand the various instances of shop floor operations, a general work routine is outlined. *A production planning list* defines jobs for the up-coming week. For each job there is a correlated production order (PO) registered in SAP. Each PO contains a full production time that includes manual time (fixed time) + cycle time per unit (=CT/article nr). *A job is run by article numbers* according to the PO, with time-estimation for the whole job time. However, X-top only logs the cycle time per article and does not include the manual time. *The planning list* in X-top is based on imported data from SAP at a certain fixed time. However, if the production schedule is updated these changes will not be shown in X-top and cause problems when logging how jobs are running in the statistics of real-time data. Hence, the two systems with different structures are not integrated to each other on a system level. When new articles are planned to be manufactured in the same machine, they do not exist in X-top, only in SAP, therefore X-top continuously needs an automated digitalized routine for detecting and measuring new jobs. Regularly, such updates are therefore communicated between Kalle and Rolle and causes instability of trusting the real operation times.

A work operation scenario at the machine: The following illustrates the operator Rolle's activities on the fiber-laser, and in the SAP and X-top systems. Rolle starts a scheduled job of 27 minutes (information from the production card). 15 minutes of the time is manual, and the rest 12 min. is laser-machine time. X-top register the manual 15 minutes as a disturbance if it is not coded. When Rolle finishes a job in practice, X-top continues to be online, i.e., X-top believes the job is on-going until the operator starts the next job. It means that the system is "operator controlled". Thereafter Rolle continues the manual work, resets fixtures, and prepares for the next job. During this time, X-top just goes on, meaning that a started job never finishes, unless Rolle interfere. Traditionally, a job is finished by registration in SAP, but in X-top there are no visible finished times unless there are coded deviations. The X-top statistics can show deviations over a period, including coded disturbances together with generic automated data (codes). Additional functionality is text-based comments for disturbances, but they are not a good source for understanding data statistics over time even because they are based on the untraceable text strings elements. Hence, the deviation code list in X-top need to be continuously reviewed during the implementation phase and discussed in the production teams, so operators and technicians knows what and how to handle deviation codes both in the system and in the work operations.

Discussion

In this paper we analyzed rich empirical data to explore how IIoT layered architectures can be aligned with user and business values in industrial manufacturing. Throughout the research our engagement in the implementation process advanced as a design-in-use approach (Islind et al., 2018; Islind et al., 2017). In contrast to a traditional separation of design and use phases (Baskerville et al., 2015) the analysis showed that RTA applications need a user-driven involvement of operators and technicians. Their roles emerged as a process of congruence between data-driven and a user-driven approach since ill-structured data analytics requires core competences and needs from shop floor workers in terms of deploying work operations in relation to the RTA application. Re-considering the data-driven design approach means to refrain from time consuming configuration efforts and quality problems to instead pay attention to user-driven needs. By analyzing the findings according to the adjusted three-layered model adapted by Al-Fuqaha (2015), diverse architecture and use issues were revealed. To complement to Al-Fuqaha's architecture, we have formulated three lessons learned that connect to the layered model. These lessons learned are considerations to be managed in order to bridge and align levels of interests both in terms of theoretical contributions to general IIoT models and of practical implications for real world IIoT implementations (Al-Fuqaha, 2015).

Lesson learned # 1 – Selecting architecture: This lesson learned alludes to issues around a common strategy on all architectural levels in the IIoT model since issues concerning the application of analytical tools stems from real-time demands on data, structure and use (Boyes et al., 2018; Trinks et al., 2017). RTA applications such as X-top are usually launched as a "Plug&Play" application that will work on top of other enterprise systems without any need to configure settings. It offers standardized, but extremely flexible structures of data and services. However, our findings showed the contingent, continuous, and non-determinate nature of deploying the RTA system as a "Plug&Play" application. To implement and configure the system is time-consuming to find the right sensors and getting the system up and running on one machine. The influence on old IT systems and its compatibility to generate data for further productive data-driven shop floor work is crucial to understand. Hence, we argue for a strategic plan with a common architecture and a well-integrated platform thinking (Boyes et al., 2018; Iftikhar et al., 2019; Verma et al., 2017). The architecture strategy needs to include knowledge on how to manage clear communication and owner relationships between production management and IT department. Also, the implementation of RTA applications creates complexity for deploying both immediate and long-term decisions based on data derived. This is not only a management and IT task anymore, rather the argument here, is to further strategize on how such system comes to play and work in practice. Hence, it is crucial that this type of strategy considers a dream team of users with knowledge and competencies of production technology and machine behavior as well as management support. Combining a well-defined architecture with defined teams and roles is needed for strategizing on how to deploy RTA applications in a data-driven industry.

Lesson learned # 2 - Harmonizing data structures: This lesson learned draws mainly on the mismatch between estimated measurement codes and real-time data. Scheduled downtime versus actual downtime, practical knowledge versus production knowledge disrupts the design and implementation of RTA applications (Madsen, Bilberg, & Hansen, 2016). The findings show that an ERP and RTA system deviates in terms of settings, key measurements, and codes. RTAs measure "real" machine time capacity continuously meanwhile the ERP delivers production plans. In the ERP system estimated full time is measured, e.g., the production time in the production order contains a full production time that includes both manual time and machine cycle time per production unit. Hence, there is a lack of feedback loops to the ERP system of the actual completion time. This effect changes due to disruptions in machine capability. Deviation codes and system-driven interruption codes should be easily summarized and reviewed. Facing daily operational problems of data consistency resulted in configurations and modifications that became directly visible in the system. Rather, the personnel need to focus on the continuous flow of real-time data and define limits, intervals, and measurements to set as actionable (Chen et al., 2012; Davenport, 2018; Trinks et al., 2017). Hence, data structures must be harmonized with current and desired definitions of data measurements and should not be restricted to the old ERP system data structure. We argue that this contributes to leverage the accurate RTA data at the exact moment to create predictive models that will generate business and user values for shop floor workers and management (Verma et al., 2017).

Lessons learned # 3 - Aligning business and user values: This lesson learned concern the congruence of the architecture and the users' work environment by aligning the RTA implementation specifically with business and user values. Having user and business values accommodated in the RTA implementation one must involve relevant users in the design process from the beginning (Islind et al., 2018). Additionally, we show how configurations of the system's data structure constantly probe changes in work operations, while at the same time being changed itself. Interrelated and time-pressured shop floor manual work and machine operations are complex and leave no room for errors in on-going production. The support and configuration work changed both regarding content and character, which demanded increasingly intertwined roles in the implementation process. The new way of working out business operations pushed most of the operators and technicians to learn how to use and exploit new possibilities in the application. Bringing the operators and the technicians into the design process also affected their acceptance later. Both operators and technicians needed to combine old experiences with new ones and some new roles were developing such as a system administrator at the local site. Hence, new skills and competences on both shop floor and management levels are acquired for the knowledge and understanding of an RTA initiative. Through our lessons learned we have argued for facilitating a bottom-up approach and letting the shop floor personnel engage in both the management of business operations (McAfee et al., 2012) and in the system configuration and harmonization of data to increase the value in a data-driven industry (Davenport, 2018).

Conclusion

This research departed from the emerging field of RTA applications that are currently adopted by the manufacturing industry in order to increase productivity and business value for a smart, data-driven industry. In sum, this paper offers a well-needed contextualization of how IIoT and RTAs are deployed in the manufacturing industry. We shed light on the way IIoT layered architectures can be aligned with user and business values in industrial manufacturing and illustrate how the implementation of RTA applications influence shop floor and manufacturing operations. More specifically, we explored the complex congruence between existing shop floor work and RTA applications, reasoning between a data-driven and a user-driven approach. The iterative and continuous work of design, configuration, and implementation of RTA applications (built on IIoT) and work operations is a distinguished feature of the design-in-use perspective, which provided insights into the complexity of the standardized RTA implementation and deployment.

We conclude that our study extends current architecture models of IIoT systems by providing concrete implications on what actions and levels needed to be considered when levering an RTA application and to align it to organizational readiness. Through the analysis of the industrial case data combined with theoretical foundations, we forwarded three key lessons learned related to the layers in Al-Fuqaha (2015). The implications from the lessons learned will also address changes on all levels in the IIoT model. We recommend the use of these three lessons learned for others that want to embark on similar RTA projects. The lessons learned might be transferrable to other industrial settings where RTA/IIoT applications are to be implemented and where there is a gap between the high-level abstraction in which application solutions operate and the low-level abstraction of industrial shop floor practices. More research and models are required to further develop and conceptualize enabling technologies for IIoT and RTA applications. For instance, studies are needed to identify incompatibility issues in more detail, for instance quantitative studies on deviation codes and measurements that verifies qualitative perceptions.

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