Knowledge Integration in Smart Factories

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Knowledge integration is well explained by the human–organization–technology (HOT) approach known from knowledge management. This approach contains the horizontal and vertical interaction and communication between employees, human-to-machine, but also machine-to-machine. Different organizational structures and processes are supported with the help of appropriate technologies and suitable data processing and integration techniques. In a Smart Factory, manufacturing systems act largely autonomously on the basis of continuously collected data. The technical design concerns the networking of machines, their connectivity and the interaction between human and machine as well as machine-to-machine. Within a Smart Factory, machines can be considered as intelligent manufacturing systems. Such manufacturing systems can autonomously adapt to events through the ability to intelligently analyze data and act as adaptive manufacturing systems that consider changes in production, the supply chain and customer requirements. Inter-connected physical devices, sensors, actuators, and controllers form the building block of the Smart Factory, which is called the Internet of Things (IoT). IoT uses different data processing solutions, such as cloud computing, fog computing, or edge computing, to fuse and process data. This is accomplished in an integrated and cross-device manner.

smart factory | cloud computing | fog computing | edge computing | knowledge integration | knowledge management | data analytics | text analytics | knowledge graph

In the wake of the Industry 4.0 development, the concept of Smart Factories and related technologies such as Cyber–Physical Systems (CPS) or the application of Internet of Things (IoT) in an industrial context emerged in the span of just ten years. Cyber–Physical Systems combine the analogue or physical production world with the digital world in a newfound complexity. Consequently, data and knowledge are playing an increasingly bigger role, supporting and leading to data-driven manufacturing (e.g., [1][2]).

Industry 4.0 has first been published on a larger scale as a (marketing) concept in 2011 at the Hannover fair in Germany. What followed was the backwards view on how to define the previous epochs of Industry 1.0 to 3.0 and their respective historical focus (e.g., [3]). Industry 4.0 presents a forward view of how the concept may be used to transform the current production environment and integrate digital solutions to improve aspects such as performance, maintenance, manufacturing of individualized products or to generate transparency over the whole production process or value chain of a company. Zhong et al. (2017) conclude that "*Industry 4.0 combines embedded production system technologies with intelligent production processes to pave the way for a new technological age that will fundamentally transform industry value chains, production value chains, and business models*" [4]. The technological advance also requires interaction with and integration of skilled workforces, even though this is often not addressed [5]. In this light, Industry 4.0 can be further defined as a network of humans and machines, covering the whole value chain, while supporting digitization and fostering real-time analysis of data to make the manufacturing processes more transparent and simultaneously more efficient to tailor intelligent products and services to the customer [6]. Depending on the type of realization and number of data sources, there might be a requirement for Big Data analysis [1][2].

Intensive research has been conducted on how to make the existing factories “smarter”. In this context, the term “smart” refers to making manufacturing processes more autonomous, self-configured and data-driven. Such capabilities enable, for example, gathering and utilizing of knowledge about machine failures, to enable predictive maintenance actions or ad hoc process adaptations. In addition, the products and services which are manufactured often are aimed to be “smart” too, meaning they contain the means to gather data which may be used to improve functionalities or services through continuous data feedback to the manufacturer.

A generic definition of the term Smart Factory is still difficult, as many authors provide definitions based on their specific research area [7]. It can be concluded from this that the Smart Factory concept is targeting a multi-dimensional transformation of the manufacturing sector that is still continuing. Based on their analysis, Shi et al. (2020) conclude on four main features of a Smart Factory: (1) sensors for data gathering and environment detection with the goal of analysis and self-organization, (2) interconnectivity, interoperability and real-time control leading to flexibility, (3) application of artificial intelligence (AI) technologies such as robots, analysis algorithms as well as (4) virtual reality to enhance “human–machine integration” [7]. To target the diversity of topics related to the term Smart Factory, Strozzi et al. (2017) conducted a literature survey of publications between 2007 and 2016 and concluded from more than 400 publications direct relations between smart factories and the topics of real-time processing, wireless communication, (multi)-agent solutions, RFID, intelligent, smart, flexible and real-time manufacturing, ontologies, cloud computing, sustainability and optimization [8], identifying main areas but also enablers for a Smart Factory.

The overall question this work tries to answer is “How do Industry 4.0 environments or Smart Factory plants of the future look like and what role does data and knowledge play in this development?” Tao et al., (2019), referencing Zhong et al. (2017) [4], summarize that “*Manufacturing is shifting from knowledge-based intelligent manufacturing to data-driven and knowledge-enabled smart manufacturing, in which the term “smart” refers to the creation and use of data*” [9]. This shift has to be considered with the help of concepts known from the disciplines of data analytics, knowledge management (KM) and knowledge integration, machine learning and artificial intelligence. It presents a change from “knowledge-based”, explicitly represented, qualitative data to the consideration of quantitative data in which meaningful patterns trigger manufacturing decisions, while being informed by supporting knowledge representations, such as ontologies. Especially the pronounced roles of data and knowledge are key aspects of future manufacturing environments and products.

Before talking more about this change the terms data, information and knowledge as well as knowledge management will be introduced briefly, giving a better background of understanding [10]: From a knowledge management perspective, the three terms are closely related, whereas data are the basis being formed out of a specific alphabet and grammar/syntax and may be structured, semi-structured or unstructured. Information builds on top of data which are used and interpreted in a certain (semantical) context, while knowledge is interconnected, applied or integrated information and oftentimes relates to a specific application area or an individual. That is why the terms of individual and collective knowledge are important factors for knowledge management, a discipline supporting, e.g., the acquisition, development, distribution, application or storage of knowledge within an organization. Different KM models or processes may be established and manage targeting human, organizational and technological aspects. Frey-Luxemberger gives an overview of the KM field [10].

The changes and role of data in manufacturing detailed above, is motivated or required by the rising customer demands of customized or tailored orders [11]. From an outside perspective the change of market demands requires hybrid solutions which not only focus on the manufacturing of physical devices or products but an accompanying (smart) service [12], which is only possible if the product generates data to be analyzed and used for offering said service. At the same time, the interconnected technologies require a change in knowledge management. Bettiol et al. (2020) conclude: "*On the one hand advanced, interconnected technologies generate new knowledge autonomously, but on the other hand, in order to really deploy the value connected to data produced by such technologies, firm should also rely on the social dimension of knowledge management dynamics*" [13]. The social dimension will be discussed later when reflecting on the changing role of employees in Smart Factories.

To meet a lot size of one, while offering extensive automated configuration abilities throughout the production process, the Smart Factory has to offer configuration and adaptation possibilities in a scalable way. At the same time these have to be manageable by the human workers, as well as being aligned to the underlying business processes. The realization is only possible by collecting and using data and knowledge throughout the manufacturing and documentation process, as well as by deploying automated data analytics and visualization tools to enable real time management and reconfiguration. It is expected that in the future workers inside Smart Factories will have to fulfill different roles or tasks in different processes or together with (intelligent) machines (e.g., [14][15]). Furthermore, instead of only administering one isolated machine, they will be supporting overarching tasks as the surveying and monitoring of interconnected production machines or plants, as well as flexible automation solutions. This again requires knowledge about inter-dependencies in the production process as well as about consequences for multiple production queues, e.g., in case of a failure of an intermediate machine. In this context the topic of predictive maintenance (e.g., [16]) is another major issue, as the gathered data inside the Smart Factory can and has to be used to minimize the times of failures in the more complex manufacturing environment, deploying analytics strategies (e.g., [16]) or machine learning algorithms to detect potential failures or maintenance measures. The concept of a digital twin (DT) (e.g., [9]) might be used here to fuse data and simulation models to create a real-time digital simulation and forecast the real environment, supporting the early detection of potential problems and real-time reconfiguration.

In the following, the different aspects of a Smart Factory including computing, analytics and knowledge integration perspectives will be discussed in more detail.

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