Big Data as a Promoter of Industry 4.0: Lessons of the Semiconductor Industry

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***Abstract*—The catchphrase "Industry 4.0" is widely regarded as a methodology for succeeding in modern manufacturing. This paper provides an overview of the history, technologies and concepts of Industry 4.0. One of the biggest challenges to implementing the Industry 4.0 paradigms in manufacturing are the heterogeneity of system landscapes and integrating data from various sources, such as different suppliers and different data formats. These issues have been addressed in the semiconductor industry since the early 1980s and some solutions have become well-established standards. Hence, the semiconductor industry can provide guidelines for a transition towards Industry 4.0 in other manufacturing domains. In this work, the methodologies of Industry 4.0, cyber-physical systems and Big data processes are discussed. Based on a thorough literature review and experiences from the semiconductor industry, we offer implementation recommendations for Industry 4.0 using the manufacturing process of an electronics manufacturer as an example.**

Keywords—Industry 4.0; Smart manufacturing, Cyber-physical systems; Semiconductor;Big data; Internet of Things

I. INTRODUCTION

Industry 4.0 is often referred to as the 4th generation of industrial revolutions [2], which began with the invention of the steam engine in the 18th century, continued with the discovery of mass production systems in the early 20th century and were followed by the development of information and communication technology in the late 20th century as a third stage [1].

The concept of and term "Industry 4.0" was introduced at the "Hannover Messe 2011" by the German government to establish smart factories "that are the ultimate realisation of Smart Manufacturing." Similarly, the United States ("Digital Manufacturing and Design Innovation" [2]) focused on programs and national strategies for "Smart Manufacturing," also referred to "advanced manufacturing" to keep up with the competition from other industrial nations. In 2014, the South Korean Ministry of Science, Internet and Communication Technologies and Future Planning (MSIP) together with the Ministry of Trade, Industry and Energy (MOTIE) announced the initiative "manufacturing innovation 3.0" to support research and development in the manufacturing domain [1]. In 2015 and 2016 China announced "2025 Plan" (also termed "Made in China 2025") and "Internet Plus" strategic plans that focused on strengthening manufacturing and accelerating service innovation [2]. The goal of these initiatives is improving main manufacturing factors, such as productivity, quality, delivery and flexibility based on technology convergence [1]. Wang and Wang [2] and Brettel et al. [3] argue that Industry 4.0 describes a combination of many concepts and technologies used in various contexts, including massive data, (Big) data analytics, cloud technologies, network security and distributed intelligence.

The next section defines the main terms and concepts of Industry 4.0, followed by an overview for the key aspects, challenges and potential promoters of Industry 4.0 in Section III. In Section IV we present Big data and the Big data process as the key enablers of Industry 4.0. In Section V we introduce the electronic industry on the example of the semiconductor industry, explain why it qualifies as an early adapter of Industry 4.0 and describe the manufacturing process of a Printed Circuit Board Manufacturer, using it as an example of the road map to Industry 4.0 in Section VI. Finally, we summarize our conclusions in Section VII and provide a future work outlook in Section VIII.

II. BACKGROUND

Many concepts and specialised terms have been introduced to describe and promote the vision of Industry 4.0. The ones listed and explained in this section were selected from the literature based on memorability and meaningfulness.

- *Industry 4.0* focuses on the establishment of intelligent products and production processes. "In future manufacturing (often called smart manufacturing), factories have to cope with the need of rapid product development, flexible production as well as complex environments" [3].
- "*Smart Manufacturing* is a collection and a paradigm of various technologies that can promote a strategic innovation of in the existing manufacturing industry through the convergence of humans, technology and information" [1].
- *Smart factory* is integrating all recent Internet of Things (IoT) technological advances in computer networks, data integration and analytics to achieve transparency at factories [4]. Smart factories represent an important element of Industry 4.0 and consist of cyber-physical systems communicating via the IoT and supporting humans and machines. [2]

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- *Cyber-physical systems* (CPSs) are a fusion of the physical and virtual worlds. [5] “In manufacturing, a CPS can combine progresses, which is achieved by large computing systems on planning, modelling, and prediction with the power of data that is generated during manufacturing processes by a lot of small data-driven devices such as actuators, sensors, or RFID readers. These devices are enabled by advances in cognitive control systems and M2M communications.” A CPS in manufacturing is also termed cyber-physical production systems (CPPS). [2]
- *Cyber-physical production systems* (CPPS) are software-enhanced machinery leveraging embedded computing power, sensors, actuators and a high degree of connectivity. “CPPS know their state, their capacity and their different configuration options and will be able to take decisions autonomously” [5].
- The *Internet of Things* (IoT) has several definitions in the scientific literature. The definition we use is the vision that all machinery and products are equipped with embedded computing devices connecting them to the internet [6].
- *Machine-to-machine* (M2M) communication offers an automatic information exchange between CPSs that constitutes the Industry 4.0 production environment [2].
- *Big data* often has contradictory definitions. The TechAmerica Foundation defines [7] big data as “a term that describes large volumes of high velocity, complex and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management, and analysis of the information.”
- Various *Big data analytics* techniques are defined in the literature [2, 7-10]. We use the definition by Gandomi and Haider [8]: Big data analytics is an “efficient processes to turn high volumes of fast-moving and diverse data into meaningful insights” to enable “evidence-based decision making” in an enterprise.
- *“Cloud manufacturing* (CM) is the cloud computing technology that is applied in the manufacturing area, which is considered an innovation of the existing manufacturing paradigm similar to Smart Manufacturing” [1]. “CM benefits from the sharing of manufacturing resources and expertise to provide consumers with enhanced experiences” [11].

While these are the most important Industry 4.0 technologies in general, there are many others, such as sensors, Smart Energy, 3D printing, etc. [1]

In the next section, we focus on the reasons for the advent, the challenges and the promotors of Industry 4.0.

III. INDUSTRY 4.0

A. Motives of the Advent of Industry 4.0

Due to high labour costs in Germany and the global competition, the high quality offered by German manufacturers does not suffice in terms of competing with low-wage countries [3]. Therefore, some of the major objectives of the Industry 4.0 initiatives in Germany are to exploit the full potential of the manufacturing industry and prepare it for a future leadership in this new type of industrialisation [5].

In modern manufacturing, product life cycles are continuously reduced due to increasingly individual and distributed production. Similarly, highly individualised products with numerous product configurations reduce the achievable lot sizes. Moreover, now customers expect orders fulfilled over the internet at short notice, with high quality standards and within short delivery times. [12]

Industry 4.0 and CPSs offer solutions to these issues. Many formally unconnected sub-systems are being connected under Industry 4.0 and CPS scenarios [2]. The communication offers the individual manufacturing machines self-awareness and awareness of the conditions of neighbouring objects, making it possible for each individual machine to organise and optimise its own work according to the global situation on the shop floor [13].

Self-awareness also means establishing or improving self-predictability, i.e., monitoring, describing and forecasting the health status of each machine by itself. The combination of status information from all self-predictive components forms the health status of a whole factory. Holistic health monitoring is an enabler of predictive maintenance, allowing to plan and execute maintenance at the best possible time. Predictive maintenance is one requirement for a dynamic production management, helping to optimise production planning and execution. All these measures are steppingstones to improving the Overall Equipment Efficiency (OEE) [9].

B. Heterogeneous Systems

A big challenge to implementing Industry 4.0 is the heterogeneity of the systems involved. One aspect of the heterogeneity is the existence of different, in part even competing data exchange standards (e.g., OPC, OPC-UA, SEMI PV02) and many proprietary, non-public standards. Additionally, there are numerous equipment manufactures that are not focused on interoperability. This results in the current shortcomings in data management, limiting the opportunities for comprehensive monitoring of the production process. Combined with others hurdles, such as financial boundaries, the missing comprehensive monitoring limits the potential opportunities [12].

C. Cyber-Physical Systems

To address the current deficiency in status monitoring in an organised and cost-effective way, Lee [4] and Wang and Wang [2] proposed a 5-level migration plan from raw data to valuable information (Fig. 1). The first “Smart Connection Level” collects pure data from various sensors. At the second “Data-to-Information Conversion Level”, the data is converted into information by extracting the actual information from the data streams. At the third “Cyber Level”, the performance of a certain machine can be compared with all other machines. Furthermore, the future behaviour of a single machine can be

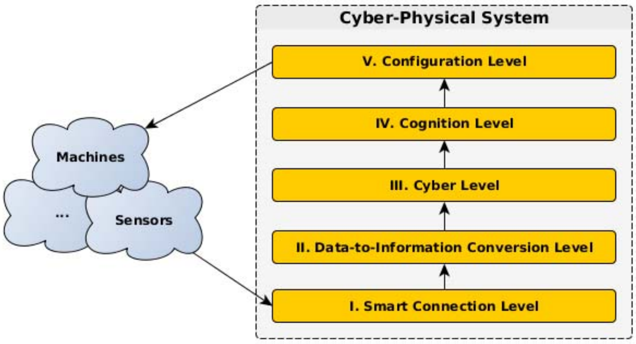

Fig. 1. The Cyber Physical System (CPS) migration plan with five levels as described by Lee [4] and Wang and Wang [2].

predicted via extrapolation from historical data. At the fourth “Cognition Level” a correlation comparison between certain components and their states throughout the factory is performed to enable better decision-making. The fifth and last “Configuration Level” closes the feedback loop by transferring actions from cyber space back to the physical world.

D. *Digital Twin*

The vision of Industry 4.0 is to create a digital twin of a manufacturing plant (or parts of it). Together they are considered a CPS. The manufacturing plant conditions are constantly replicated in the digital model. The digital model is used to test numerous parameter settings and complete scenarios in a fast and cost-effective way. Such scenarios might include improving the existing processes, changing the processes or introducing completely new processes. This way, when alterations or new processes are introduced in the physical word, they are already verified and tested via the simulation. Moreover, if the development of the digital and physical worlds diverges, it indicates a maintenance need in the physical world [2, 14].

To accomplish the transformation from the physical to the digital or cyber world, massive amounts of data must be analysed and managed. To this end, Big data and the Big data process are key enablers of Industry 4.0 (see discussion in the next section).

IV. BIG DATA

A. *Definition of Big Data*

The term “Big data” can be misleading. While the size or volume of data in question may be important, it is by far not the only crucial aspect. Multiple publications address the components and definitions of Big data [8]. A common definition aligned with the challenges and opportunities of Industry 4.0 was created by Gartner IT Group [15]: “Big data is high-volume, high-velocity and high-variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making.” “Volume” refers to the magnitude of data (the size) and “Velocity” indicates the speed at which the data is created and analysed. “Variety” describes the various types of data, namely structured (e.g., tabular data, such as database tables), semi-structured (e.g., XML and its derivatives) or unstructured data (e.g., sensor data, social media). Additionally, IBM [16] defined a fourth dimension “Veracity” which represents “the unreliability inherent in some sources of data” and deals with imprecise and uncertain data. “Veracity” could generally be viewed as the “data quality” aspect in data. An additional Big data dimension is "Value," as introduced by Oracle [17]. In the beginning of a data collection pipeline, the collected data has a relatively low value. Further into the pipeline, the processing and analysis of large volumes of data reveals information of high value, which was initially hidden in the raw data. Casually speaking, value represents the insights obtained by applying Big data analytics and is, in essence, the most important dimension of Big data.

When discussing Big data, Apache Hadoop is often used as a synonym. In fact, Hadoop is a Big data platform that has developed from a sophisticated framework to a mature ecosystem for handling massive amounts of data. [18]

B. *Big Data Process*

The Big data process are guidelines that formally describe the methods and best practices for extracting knowledge from data. Gandomi and Haider [8] divide the Big data process into two main sub-processes consisting of five stages (Fig. 2).

The Big data process strongly depends on the various Big data analytic techniques, including pattern detection, correlation analysis, predictive analytics and dashboard or report generation [8].

The output of these Big data analytic techniques is valuable knowledge, forming a solid basis for decision making and offering support to human experts in the manufacturing industry. One of the potential early adaptors of Industry 4.0 is the semiconductor industry (a part of the electronics manufacturing industry).

V. ELECTRONICS MANUFACTURING INDUSTRY

A. *Semiconductor Manufacturers as Early Adopters*

Semiconductor manufacturing is a capital-intensive business, mainly due to expensive machines that may cost up to 100 million US Dollars [19]. As Chen-Fu et al. ([19], p.30) pointed out, the “manufacturing process is very complex due to the reentrant flows in combination with very long cycle times and the multiple sources of uncertainty involved.” These issues and rapid changes in this sector often make the forecasts inaccurate.

A combination of all of those factors make the semiconductor industry a very complex field for supply chain management.

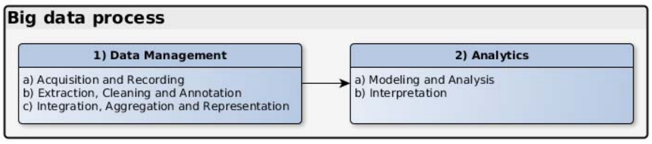

Fig. 2. The Big data process is split into data mangment and analytics. It consists of five steps.

Hence, modelling and analysis that are successful in the semiconductor industry are likely to be successful in other industrial areas [19].

Compared with other manufacturing industries, the semiconductor industry made an early introduction of end-to-end defined standards for equipment interfaces. The development of these standards began in 1980s, consolidated under the patronage of Semiconductor Equipment and Materials International (SEMI). First, standard interfaces for production components and measuring systems were developed. Collectively termed as “Semiconductor Equipment Communication Standards” (SECS), these standards regulate not only the communications between the production components on a production site but also the condition of the facilities [12].

These established standards created similar IT architectures across semiconductor factories of different operators. This is a clear advantage over the classical automated manufacturing industry, representing great potential for early adapters. Since the semiconductor industry is part of the electronic industry, transferring knowledge to other parts of the electronic industry is feasible and will be demonstrated using the example of an electronics manufacturer in the section below.

B. Manufacturing Process of a Printed Circuit Board

The company we chose as an example is one of the biggest printed circuit board (PCB) manufacturers in Europe. A generic manufacturing process for PCBs was described in detail by LaDou [20] and Crama et al. [21].

The PCB is responsible for electrical connections between the components, mechanical support for the components, reliable contacts between the components and the solder surface, and corrosion protection for connection pads [20, 21].

The PCB manufacturing consists of the tree main processes: data processing, production and finishing. Data processing is triggered by receiving a customer’s request containing the parameters of the required product. In response to each request, individual offers are made to the customer. Data processing is a prerequisite for the production and delivery of tailored PCBs. A core step for manufacturing of PCBs, the production process consists of various tasks, which are repeated multiple times until the requested amount of conductor and isolation layers are applied to the base material. Modern PCBs contain up to 28 conductor layers stacked on top of each other with isolation layers in between.

The production process from the base material (typically resin-impregnated glass fibre sheets) to the final a PCB consist of six major steps. Due to the complexity of these steps, each step is conducted by a dedicated department:

1) Photo: a conductor and isolator structure is applied to the PCB in an photoengraving process. The PCBs contain the desired conductor and isolator structure of the initial one after this process is finished.

2) Automatic Optical Inspection (AIO): the conductor and isolator structure on the PCB is automatically tested and verified.

3) Pressing: multiple layers are pressed on top of each other and mechanically fixated.

4) Machanical drilling: openings for elctrical connections are drilled.

5) Laser Drilling: delicate structures and thin holes are created using laser beams.

6) Electroplating: electrical connections between the layers and connections pads are applied to the PCB.

These six steps are repeated multiple times when multilayer PCBs are manufactured.

The final step “Finishing” begins by applying additional coating to protect the surface of the already-functional PCBs. Before the boards are delivered, two final testing procedures are conducted. Lastly, the boards are delivered to the customer and the electronic components are soldered onto the PCBs.

The following section describes a road map to Industry 4.0 for this process based on the brief outline of PCB manufacturing above.

VI. ROADMAP TO INDUSTRY 4.0

A. General Remarks

The International Roadmap for Semiconductors (ITRIS) [10] defines dimensions in accordance with the five Vs defined in Section IV. Since these five dimensions may affect each other, a company has to consider all of them to extract relevant knowledge out of their data.

This section contains a proposal for the implementation of CPS in the PCB manufacturing. Each PCB production step described in Section V.B is carried out by a dedicated department, with multiple different, very expensive machines. The machines are not strictly placed in a production line, but are organised in a so-called “island” system, meaning that the PCBs can be transferred freely between the individual islands. Nevertheless, the process steps have to be carried out in a defined order. Since there many different machine types are involved, an additional degree of freedom in scheduling can be achieved.

B. Roadmap

We propose to begin the migration to Industry 4.0 in single department (the Photo department) with only one instance per machine type. This first migration will be our test case, offering valuable feedback on the future migration of other instances of each machine type.

The migration commences on the first level of CPS by establishing a connection to the data sources. Even during this partial migration, high volumes of data can be created with a high velocity on the smart connection level. In many cases, traditional Relational Database Management Systems (RDBMS, e.g., Oracle Database) may not be able to handle the collected data volumes. The Hadoop Distributed File System (HDFS) is capable of storing large amounts of data using commodity hardware arranged in a cluster. Although a switch to a HDFS-based storage is a big move, it offers scalability and flexibility [10]. Apache Hadoop provides the functionality for importing and converting data from the existing central RDBMS of many different formats [22].

Concerning the Big data process, the first level of CPS presents the acquisition and recording part of data management sub-process. Fig. 3 shows a graphical representation of the interconnection of CPSs to the Big data process.

On the second level of CPS, data from sensors on all effected equipment are collected and aggregated to calculate the overall machine status. The collected and processed data can henceforth be used to identify malfunction of a certain machine. With regard to the Big data process, this level also provides extraction, cleaning and annotation of the collected data.

The objective of the third CPS level is to compare the machine performance. As the introduction of a CPS proceeds, at least one instance of each machine type should be connected. It is important to consider the complete manufacturing chain. Connecting all types paves the way to connecting multiple instances of each machine type. By analysing data for multiple instances of the same machine type differences in the performance of machines can be identified, which is a first important step for predictive maintenance. In terms of the Big data process, this level represents integration, aggregation and representation within the data management sub-process.

The three levels discussed so far can be applied to analyse and model an overall account of a department or complete factory. On the fourth CPS level, the complete manufacturing process can be modelled and analysed and correlations between the different machines can be established. For example, if the results of the photo units are not acceptable and no misconfiguration is apparent, the results of the preceding steps can be investigated by performing root cause analysis and the needed to adapt parameters of the machines involved in earlier stages of the production can be identified. Furthermore, level four enables a comparison between departments. For example, if the AOI and the photo department are connected to the CPS, the results for the AOI department can be correlated with the parameters of the different machines to model department-comprehensive impacts. The fourth level partially corresponds to the modelling and analysis in the analytics part of the Big data process. Together with the final level, the fourth level partially represents the interpretation step in the analytics sub-process in the Big data process.

The fifth and last CPS level is the most sophisticated one. It involves closing the feedback loop between the digital model and the real manufacturing equipment. Depending on the process and potential application, the feedback loop may either be fully automated or require human interactions. At this level, there is a considerable difference between the CPS and the Big data process model. While the CPS aims for a fully automated configuration level, the interpretation step for the same layer foresees human involvement rather than an automated feedback.

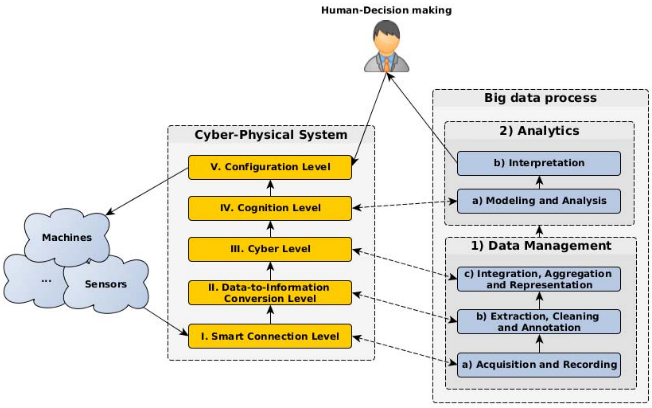

Fig. 3. Cyber Physical Systems (CPSs) and the Big data process have many similar tasks. Correltated conceps are connected by a dashed arrow. CPSs are desiged to have an automated feedback channel into the physical world. In the Big data process, this feedback loop is closed by humans.

C. *Off-Line vs. On-Line Analytics*

On-line data collection refers to a CPS with all data collection and analysis synchronised via the data emitting processes. Off-line data collection refers to data collection and analysis with a time-shift to the emitting processes. Most commonly, off-line analytics can be executed by transferring data from the existing systems into the new infrastructure for performing the analysis. One major goal of Industry 4.0 is the setup of a CPS to real-time processing, storage and analysis of massive, high-dimensional data with a low-quality or low-information content collected by CPS sensors. On-line processing of high dimensional and low-quality data is a big challenge. [2]

With respect to the proposed migration plan, the integration should start with only off-line analytics. The data collection should be implemented by recurring, batch-based import from the existing systems. Using these data, structures, analysis, and models up to the fourth level can be created. These off-line data analytics should provide a base for the implementation of the full “on-line” system after the fifth level is realised. The implementation of the fifth level establishes on-line feedback capabilities and is the final and crucial step for a system working on all five levels.

VII. CONCLUSION

In this paper, we presented an overview of the history, concepts and technologies of Industry 4.0. CPSs are a key enabler for Industry 4.0. To gain insights from massive amounts of data collected by CPSs, the Big data analytics process is required. One of the biggest obstacles to collecting vast amounts of data via CPSs is heterogeneity of system landscapes, with various machine standards, manufactures and equipment maturity. We presented a roadmap for converting an electronics manufacturer to an Industry 4.0 enterprise. To illustrate our approach, we described the production process of a PCB manufacturer. Our roadmap focuses on the manufacturing process in combination with different layers of a CPS. To facilitate the implementation of a CPS in a manufacturing enterprise, we discussed the differences between off-line and on-line analysis and provided guidance for the corresponding transition.

VIII. FUTURE WORK

In the course of the European joint project SemI40, we will implement parts of the proposed roadmap and use a CPS to transform an electronics manufacturer into an Industry 4.0 enterprise. Preliminarily studies of the areas that are suitable as a starting point are currently under way. After defining a potential candidate, a case study will be undertaken to implement the first stages of the roadmap in the selected area. The prototype will be used to investigate the benefits and drawbacks of the introduction and operation in an Industry 4.0 environment. This study will help to improve the running system and the defined roadmap to realize the full potential CPS of the proposed roadmap in future implementations.

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