Making Sense of Manufacturing Data

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Keywords: Industry 4.0, Smart Manufacturing, Digital Factory, Big Data Analytics, Data Science.

Abstract: A fast and successful digitation of the industry is meant to be a key issue for Europe in order to maintain its leading role. The new industrial revolution will be based on data as raw material, where the digital economy will merge as a real economy. The challenges for a "hard" sector where traditionally the "soft" has not been considered as an asset are evident and notorious. In this paper IK4-IDEKO, as part of a machine tool builder group, DANOBATGROUP, provides a vision of the challenge and the approach for the solution, supported by results of the current work.

1 INTRODUCTION

The new industrial revolution, nowadays called Industry 4.0, pursues the adoption of Cyber Physical Systems (CPS) to enable the creation of a real-time, precise, reliable, monitoring system able to feed analytics solutions to support the automation, the control, and the improvement of the implemented business processes. With respect to the current solutions, pervasiveness of the Internet of Things together with the ability to manage and process bigger amount of data in real-time, makes the Industry 4.0 a paradigm that can bring a lot of advantages in the Factories of the Future: e.g., more detailed control of processes and ability to quickly react to internal and external changes.

The Industrial Internet is an internet of things, machines, computers and people, enabling industrial operations using advanced data analytics for transformational business outcomes. There are many interconnected systems deployed today that combine hardware, software and networking capabilities to sense and control the physical world.

With the development of the IIoT and connectivity and the cloud computing infrastructures provided as a service, a huge amount of data comes up in order to boost new business models supported in the data analytics. Figure 1 shows the three main pillars of innovation and transformation in manufacturing based on IT. The connectivity capabilities provided by the development in IIoT, supported more and more in standards like MTConnect or OPC-UA are a straightforward way to listen to industrial devices, that are becoming energy efficient and accessible wireless. In a parallel way, the Platform as a Service and the cloud computing models are offering ubiquitous storage and computational resources, federated and hybrid topologies, for the IIoT data. This data will be converted in value, if we are able to benefit from Big Data Analytics, creating business models based in smart services. The loop with the IIoT is closed in the extent that smart services can be implemented as actuators with intelligent CPSs.

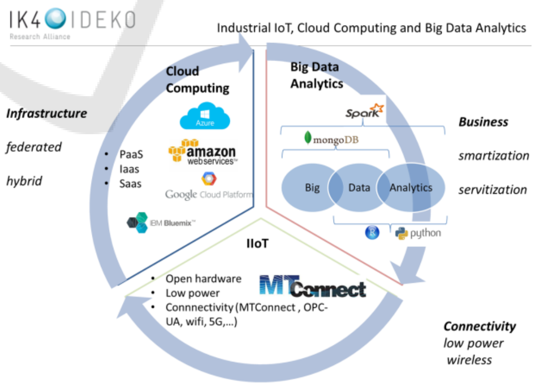

Figure 1: IIot, Cloud Computing and Big Data Analytics.

So far, there is actually a real world, represented by the automation pyramid, where there are different levels: sensors and embedded systems, cyber-physical components, machines, production lines and factories. This real world has a twofold representation in the data realm, represented as a virtual world (Figure 2).

Gerrikagoitia, J., Unamuno, G. and Sanz, A.
Making Sense of Manufacturing Data.
DOI: 10.5220/0005999005900594
In *Proceedings of the 13th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2016) - Volume 2*, pages 590-594
ISBN: 978-989-758-198-4

In this sense, the Industrial Internet embodies the concept of “data factory”, where data is produced, moved, exchanged, transformed, processed, elaborated and visualized in the virtual world, where the digital domain takes its shape to take data into action and value.

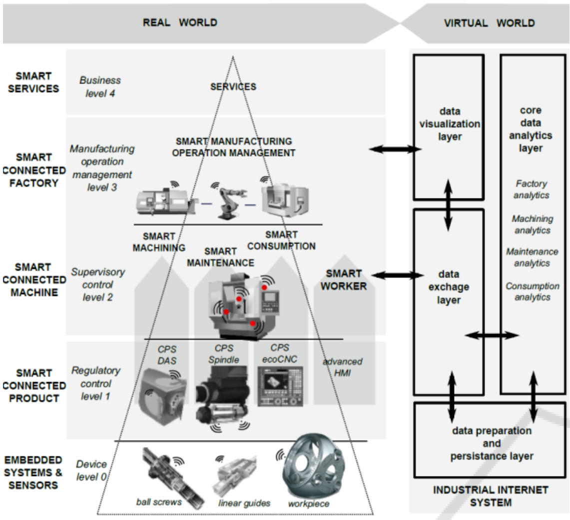

Figure 2: Real and virtual world in manufacturing.

This way, data becomes a real asset even for industrial organizations and decision makers are starting to be sensitive to this new paradigm in which the big data analytics and data science open new opportunities based on “smartization” and “servitization”.

2 THE PROBLEM

Manufacturing firms not only seek manufacturing technique innovations but are also beginning to focus on added value services and new business models, creating a fuzzy boundary between manufacturing industry and service industry.

Servitization was proposed by Vandermerve and Rada in 1988 (Vandermerwe and Rada, 1989). They emphasized the concept of customer focus; combining products, services, support, and knowledge are the most important elements. Furthermore, the authors also asserted that not only service industries, but also manufacturing industries should focus on innovative value added service development in order to quickly enhance their core competencies. Baines defined manufacturing servitization as innovation of organizational capabilities and processes, from product sales to integrated product services (Baines et al, 2009). Servitization is defined as the strategic innovation of an organization’s capabilities and processes to shift from selling products, to selling an integrated product and service offering that delivers value in use, i.e. a Product-Service System (Martinez et al., 2010).

The concept of a Product Service-System (PSS) is a special case of servitization. Mont defines PSS as a system of products, services, supporting networks, and infrastructure that is designed to be competitive, satisfy customers' needs, and have a lower environmental impact than traditional business models (Mont, 2004). In the PSS business model, industries develop products with value-added services, instead of a single product itself, and provide their customers with services that are needed. In this relationship, the market goal of manufacturers is not one-time product selling, but continuous profit from customers by total service solution, which can satisfy unmet customers’ needs. For a best viewing experience the used font must be Times New Roman, on a Macintosh use the font named times, except on special occasions, such as program code (Section 2.3.7).

3 PHILOSOPHY

In order to address the explained challenges IK4-IDEKO has defined a data management framework shown Figure 3.

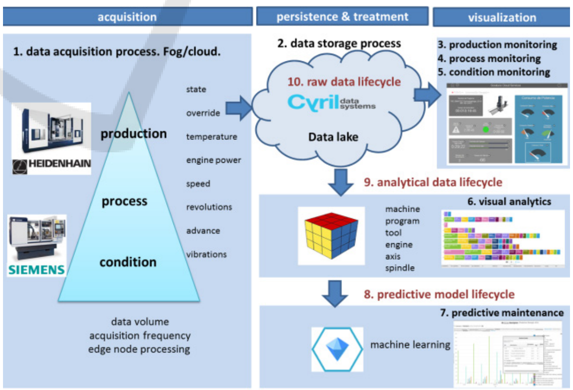

Figure 3: Data management architecture.

The three main layers of data acquisition, data persistence and visualization have to be designed having in mind that data is a raw material provided by machines.

3.1 Data Acquisition Layer

The data acquisition layer is responsible of the observation, gathering and delivering of the variables of the machine to the persistence layer.

The general solution provided by IK4-IDEKO is a device and software built jointly with Cyril data systems (www.cyril.es) that is able to connect via Ethernet to different types of machines, read data and sends them to the cloud. This data gathering device can connect to diverse numeric controls as Heidenhain, Fanuc or Siemens, or even a data gathering sensors.

Once the device is connected to a machine, a web management tool can be used to remotely configure the device, define the signals or variables that will be read from the machine etc (Figure 4). In this case, the memory address map of the PLC will be used to match the real world with its corresponding virtual counterpart. Moreover, the sampling or data gathering frequency has to be defined, in that sense, the concept of group of capture has been defined, in order to read and transmit together the set of variables that have the same observation frequency.

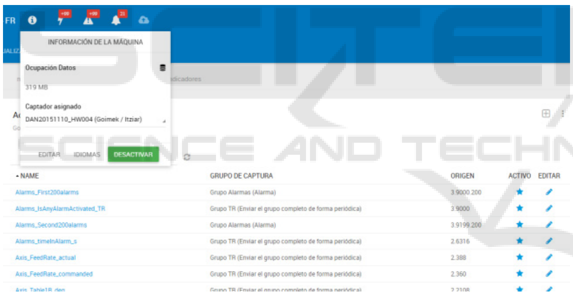

Figure 4: Remote configuration of PLC variables.

The commonly available variables of a machine tool are obtained through the numeric control and the programmable logic controller (PLC). These components manage a wide set of variables that can be categorized in the following groups: state, alarms, speed, temperature, power, revolutions per minute, advance,… All these variables are related to the machine or to specific components as engine, axis, spindle, tool,…

Other useful variables that can be obtained are related to the interaction of the worker with the machine as the different types of overrides, modifying the programmed operation behaviour, interruption of the cycle of the machine etc. Although the numeric control is the main data acquisition device, there are other variables, for example the ones related to dynamics, like vibrations that have to be obtained using specific sensors. This way, the monitoring of the machine implies the monitoring of a numeric control, PLC and sensors, depending on the observational requirements.

3.2 Data Persistence Layer

The management, transformation and treatment of the data is the most important stage in a data-driven approach in order to make sense of a myriad of variables (temperature, speed, override, power, revolutions, vibrations,…) obtained from cnc/plc and a set of sensors.

The data persistence layer is divided in two parts. First, a data lake model is the general repository where the data from the different groups of capture and sensors is stored and tagged using metadata in order to provide data lifecycle and management capabilities. A NoSQL document oriented MongoDB database is used for this purpose.

The second part of the persistence layer is an analytical database based on a data mart model. The initial implementation relies on a PostgreSQL relational database management system with three datamarts: production, process and condition.

The whole set variables of a machine can be grouped conceptually in production, process or condition data. The production variables focused in the state of the machine and closely related to the concept of availability. Process variables provide information about the machining process through speed, temperature, power, revolutions,…process and production can be used to approach the overall equipment efficiency of the machine in a great extent. The third group of condition monitoring variables, besides cnc variables, vibration, noise, and temperature measurements are often used as key indicators to provide health information about the machine and help detect machine faults early, which prevents unexpected failure and costly repair.

The dimensional model of the data warehousing conceptual framework has been used because the observed variables make more sense once they are organized and combined with dimensions, like machine, program, tool, engine, spindle…

3.3 Data Visualization Layer

The visualization layer is divided in two parts.

The first one is machine monitoring. The information is shown in real time, the monitoring can be about production (state, alarms), process (current machining process) and condition (health and symptoms).

For this purpose, IK4-IDEKO´s strategy is based in a web interface generator, a toolbox with different visualization widgets is available and ad-hoc windows can be designed by the end users. A process monitoring interface is displayed in Figure 5.

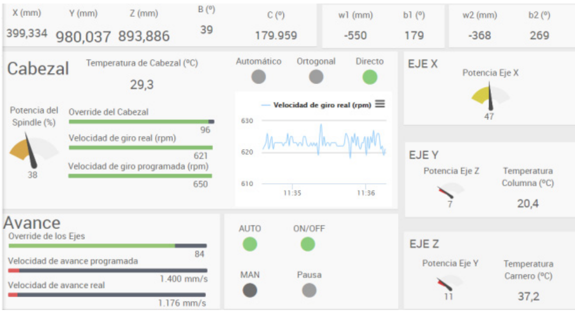

Figure 5: Process monitoring.

For this scenario, the data lake provides the real time stream data to be presented via web.

The second part of visualization is focused in visual analytics and insights in order to enhance the EDA (exploratory data analysis) and communication tasks of the data scientists. For this purpose third party tools are used, mainly RStudio, Watson Analytics and Qliksense (Figure 6).

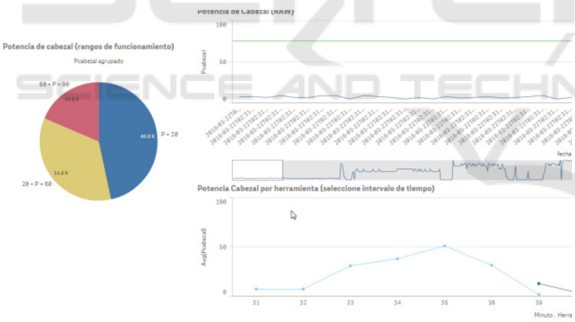

Figure 6: EDA using third party tools.

The data marts are the data source used in the case of the exploratory data analysis visualization and machine learning modelling for production, process or condition data.

4 CONCLUSIONS

The digitization of the industry in order to boost and benefit from digital opportunities requires a mid-term transformational roadmap. Nevertheless, to move forward in that way, certain steps have to be done in the right direction. There are key enabling technologies such as IIoT connectivity, cloud computing and big data analytics as drivers for making sense of manufacturing data. This paper shows the way that IK4-IDEKO is approaching the challenge of digitizing the manufacturing industry.

If data is the raw material of the new industrial revolution, the data science in manufacturing is what definitely will help to make sense of manufacturing data. A machine-centric data-driven approach that benefits from IIoT, cloud computing, Big Data and visualization technologies and empowers the role of the data scientist in manufacturing.

The consumption, use and creation of innovative digital services is being leveraged by the this new role that is gaining prominence in organizations: the data scientist. Data scientists are the people who understand how to fish out answers to important business questions from today's tsunami of unstructured information (Davenport and Patil, 2010). As companies rush to capitalize on the potential of big data, the largest constraint many face is the scarcity of this special talent. What kind of person does all this? What abilities make a data scientist successful? The data scientist can be understood as a hybrid of data hacker, analyst, communicator, and trusted adviser. An extremely powerful combination. As this multidisciplinary role is difficult to get in a single professional, IK4-IDEKO has created a Data Science in Manufacturing Team with the vision and ambition to become a reference group in this new knowledge area. Computer scientist, electronics, mechatronics, experts in industrial automation, dynamics and control, production systems, machining processes, … related skills put together to find a story in a data set and provide a coherent narrative about a key data insight with the idea to convert data in value and an eventual business exploitation model.

ACKNOWLEDGEMENTS

ELKARTEK, Basque Government Research Program

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