Multi-Loop Feedback Hierarchy Involving Human Workers in Manufacturing Processes

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Abstract

In manufacturing environments today, automated machinery works alongside human workers. In many cases computers and humans oversee different aspects of the same manufacturing steps, sub-processes, and processes. This paper identifies and describes four feedback loops in manufacturing and organises them in terms of their time horizon and degree of automation versus human involvement. The data flow in the feedback loops is further characterised by features commonly associated with Big Data. Velocity, volume, variety, and veracity are used to establish, describe and compare differences in the data flows.

1 Introduction

A modern manufacturing process involves human workers, robots, computers, and information systems in various combinations, depending on the degree of automation (Henriques et al., 2013). Successful manufacturing businesses manage their processes by collecting information from all actors involved. This requires the support of Information and Communication Technologies (ICT) to manage the organisational, technical, and human aspects involved (Kurgan and Musilek, 2006). This paper characterises the evolved feedback loops in controlling a manufacturing process depending on their time horizon and the data involved. The authors identified feedback loops and their characteristics as part of the SemI40[1] project, based on observations form the literature, and earlier research projects. Feedback loops, sometimes termed feedback cycles, use the output of a system to control its input. They occur

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in nature and have been used for over 2000 years for controlling many technical innovations, from the steam engine to modern automation engineering. (Bennett, 1996)

The manufacturing domain is a highly completive market with value chains and enterprises spreading around the globe (Cusmano et al., 2010). To gain advantages over their competitors, manufactures have often relied on technological advances. In the 18th century the steam engine was invented, leading to mechanisation and the first industrial revolution. The second industrial revolution began with the introduction of mass production in the form of assembly lines and the use of electricity in the first half of the 20th century. Computers, digital controlled machines, and the uprising of automation in manufacturing initiated the third industrial revolution. As of 2010, omnipresent digital networks, cheap data storage, and cheap digital processing power sparked the fourth industrial revolution and the vision of Industry 4.0 as interconnected Cyber-Physical Systems (CPS). (Kagermann et al., 2013; L. Wang and G. Wang, 2016)

Automation and modernisation have always been driven by the strongly competitive manufacturing business (Tracey et al., 1999). Due to financial and organisational barriers, companies cannot take advantage of all opportunities provided by new technologies and have to innovate on a gradual and evolutional basis rather than in an abrupt and revolutionary way (Henriques et al., 2013).

The historical development will be described in the next section in more detail, followed by a brief introduction of main aspects of Big Data. Section 3 characterises the feedback loops established to control manufacturing steps, sub-processes, or complete processes and describes the data in the feedback loops by comparing them to criteria from the Big Data domain. The last section summarises the ideas presented in this paper and provides an outlook of possible future work.

2 Related Work

2.1 Technology-Driven Changes in Manufacturing

Well-established manufacturing businesses contain a mixture of ICT equipment, partly or fully controlling manufacturing processes some of which may have been established decades ago. This is the result of a historical development driven by the change from mechanical to ICT technology. During the second industrial revolution in the first half of the 20th century, manufacturing was dominated by Taylorism and the replacement of human labour by machines, leading to a high degree of standardisation, automatic control, and first automation. From the 1950s to the 1970s, first computerised and programmable machines were introduced into manufacturing lines, offering Numerical Control (NC), Computer Numerical Control (CNC), transfer lines, and Materiel Requirements Planning (MRP) technologies. They can be viewed as transitional technologies on the way to the third industrial revolution with its computerised automation. In the 1970s and 1980s, digital communication networks emerged and offered Distributed Numerical Control (DNC) and Flexible Manufacturing Systems

(FMS) controlling multiple machines at once. Moreover, the design phase became digitally linked to manufacturing via Computer-Aided Design (CAD), Computer-Aided Manufacturing (CAM), and MRP II, fully embracing the third industrial revolution. (Johansen et al., 1995; Lee, 2015; Lefebvre et al., 1996; Marri et al., 1998)

Harrington (1974) first mentioned Computer Integrated Manufacturing (CIM) as the vision of a fully computerised and connected manufacturing exchanging information with the surrounding disciplines, such as design, material supply management, and connected partner companies. A complete implementation of CIM leads to automation of the entire information flow in a company, from the receipt of an order, over the entire value chain and to shipping of the finished order. (Johansen et al., 1995; Lefebvre et al., 1996; Marri et al., 1998)

The subject of connecting manufacturing components is still an open research and engineering issue. It reaches beyond the third industrial revolution and is part of such initiatives as Industry 4.0, in which this idea is regarded as a central element of the fourth industrial revolution (Almada-Lobo, 2016). Industry 4.0 introduces Internet technologies into the manufacturing industry and should make factories independent, smarter, and connected. This facilitates a closer collaboration of human workers and automated machines (L. Wang and G. Wang, 2016).

The connection aspect is a vital requirement for cyber-physical systems (CPS), which are key-enablers of Industry 4.0, connecting the cyber to the physical world. In the manufacturing domain, CPS map actions taken on shop floor into digital systems by providing each physical entity (e. g., component or machine) with a corresponding digital twin. (Almada-Lobo, 2016) This digital representation of the physical world offers new opportunities by further increasing possibilities of monitoring, steering, and controlling the manufacturing process. Furthermore, it is possible to test new configurations and process adaptions using the digital twin by means of simulation before implementing them in the physical world. In this respect, CPS also provide many options for testing scenarios and performing simulations (L. Wang and G. Wang, 2016).

The result of implementing the Industry 4.0 paradigm via CPSs is a Smart Factory. By incorporating computer networks, data and analytics, smart factories create transparency on manufacturing shop floors (Lee, 2015). However, the ultimate goal of Smart Factories announced by the German Federal Ministry of Education and Research takes these ideas one step further: Smart Factories represent the vision of production environments that can completely self-organize due to self-awareness and self-predictiveness of machines and workers. In order to fully exploit this potential, highly sophisticated data analysis and data management concepts are required to create an autonomous system. (Kagermann et al., 2013)

2.2 From Data to Actionable Knowledge

To achieve autonomy, Smart Factories need to extract reliable information from raw data. Comprising efficient processes that turn high volumes of fast-moving and diverse data into meaningful insights, Big Data processes enable evidence-based decision making by. Big Data has many aspects, most commonly including data volume (magnitude of data), variety (structural heterogeneity of data), velocity (rate and speed at which data is generated), veracity (unreliability inherent to some sources of data), and value (raw data has low value relative to its volume but can provide the foundation for many business cases) (Gandomi and Haider, 2015).

The volume, variety, velocity, and veracity features of Big Data are the obstacles to deriving the data value. Various processes have been outlined to extract value from the data, with either a more industrial or a more scientific emphasis. These processes consider the entire chain of knowledge extraction, data management, development of specialised algorithms, data interpretation, visualization of results, and modelling and supporting the interaction between humans and machines. Most of these processes are highly iterative and involve multiple loops between their stages. Furthermore, human involvement is vital to some the feedback loops, e. g., training, assisting, and using self-adapting systems learning in each iteration. (Kurgan and Musilek, 2006) Similarly, feedback loops can be identified in manufacturing, where they are used to control the manufacturing process as shown in Figure 1. The next section describes these feedback loops and the data involved in detail.

3 Multi-Feedback Loop Architecture

Feedback loops are crucial to making a step from pure observation to informed decision making and control, connecting the physical with the cyber world. Hence, these feedback loops are not unique to the knowledge or value extraction processes and can also be found in CPS and other modelling domains (Al-Hammouri, 2012). In this section, feedback loops inherent to manufacturing businesses are presented and characterised. Figure 1 depicts the scenario in a modern manufacturing environment, under which individual steps, sub-processes, or

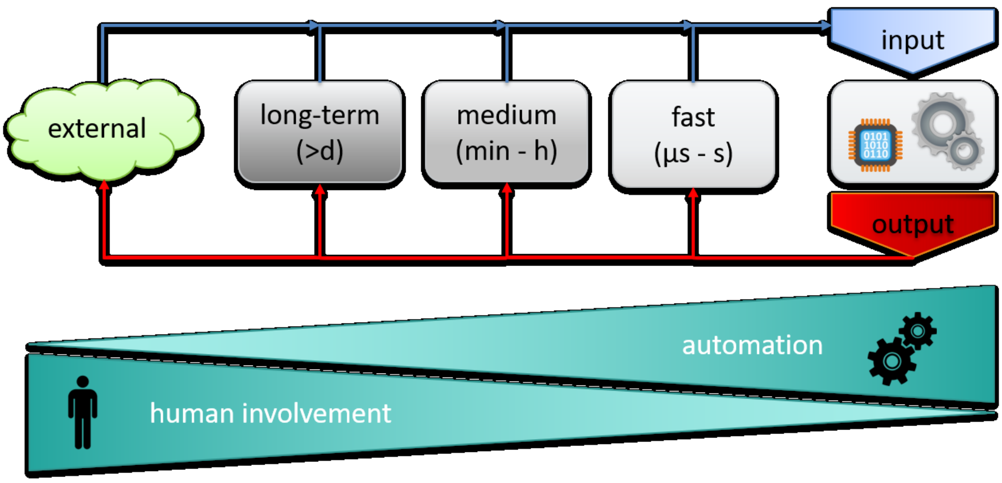

Figure 1: The input and output of a manufacturing step, sub-process, or process are controlled via feedback loops with various time horizons and a varying degree of automation.

complete manufacturing processes are subject to many feedback loops with various time horizons and various actors involved. At the centre of each feedback loop is an individual step, sub-process, or a complete manufacturing process with all its required input and output, as shown in Figure 1. Four feedback loops with various time horizons and varying degree of automation connect the outputs to the required inputs.

Fast The fast loop is the closest one to the observed process or process step and works in very fast cycles in the range of microseconds to seconds. It is characterised by a high degree of automation generally controlled by embedded computer systems in the manufacturing equipment. An example would be the movement control of a robot arm following a predefined trajectory. This feedback loop is essential to any controlled manufacturing equipment and can already be found in the early NC and CNC machines.

Medium The medium or intermediate loop operates in cycles of minutes to hours. An example of feedback loops in this cycle would be checking semi-finished products and adapting process parameters to varying input material qualities. In addition, repair, and retooling fall into this loop. This loop is typically operated by computer systems or workers on the shop floor. The degree of automation in this cycle may strongly vary depending on the manufacturing domain. Automation at this level began with the introduction of DNC and FMS systems.

Long-Term The long-term loop has a time horizon of one or more manufacturing days or shifts. Decisions within this cycle are generally made by humans in meetings. Hence, human involvement in this cycle is very high and the degree of automation is very low. Information from surrounding disciplines is an essential part of this feedback cycle.

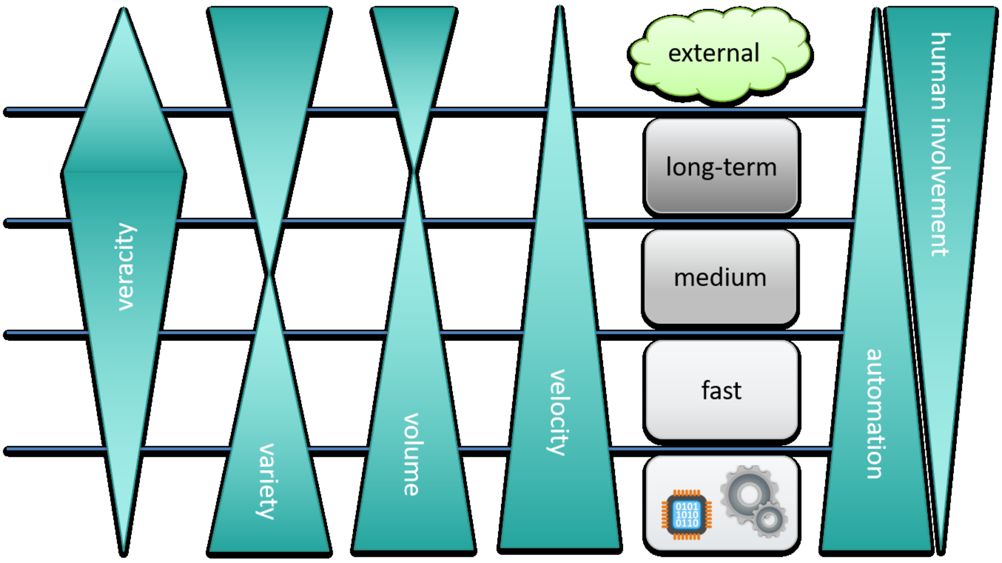

Figure 2: The individual feedback loops differ not only in their cycle times but also in terms of data velocity, volume, variety, and veracity, which are features form the Big Data domain.

While such decisions are still predominately made by humans, automation at this level has already been envisioned in the CIM. Nevertheless, incorporating expert knowledge and plausibility checks still require a large contribution of human working time.

External The external loop closes the feedback cycle with the supplier and customers of a company. It includes the automatic processing of incoming orders, commissioning of manufacturing, and ordering of supplies. Although this aspect has already been envisioned in the CIM, it is still heavily dominated by human-to-human interaction.

The described feedback loops characterise the manufacturing process in operation. Installation of a new production line falls outside of the normal operation, but might also be associated to the external or long-term feedback loop, based on the degree of automation and the involved parties.

The presented feedback loops differ not only in terms of their cycle times but also with regard to the distinguishing features of Big Data velocity, volume, variety, and veracity as depicted in Figure 2.

Velocity declines along with the automation to suite the human involvement.

Volume decreases with the degree of automation and the increase of human involvement but rises again relative to the external feedback loop. The volume decrease follows the cognitive capabilities of humans. If humans should make decisions based on raw data, it would have to be reduced and represented in a way feasible for human interaction. The increase in data volume in the external loop is caused by the overhead of working with other departments or other companies, obstructing collaboration with external partners. However, this is an opportunity for further automation, even across departmental or company boundaries.

Variety has a necessary minimum in the medium feedback loop representing the common communication or the data storage backbone, which is a necessity for unifying the information exchange within larger parts of a company. Although one common communication and storage backbone rarely exist in real word systems, synchronisation between different systems can generally be assured in the time horizon of minutes to hours matching the medium feedback loop. From this minimum, there is an increasing variety in either direction. Towards the faster loops the variety is caused by different automation standards and toward the long-term and external loop the variety is caused by different data exchange formats and visual representations.

Veracity peaks in the long-term feedback loop. Glitches and errors from the faster layers are detected and sometimes corrected in the long-term loop by the redundancy created during the investigation of larger data samples, merging various data sources, and human expert knowledge. The department or company boundaries create inconsistencies in data handling. Combined with a lack of expert knowledge exchange over the said boundaries, this results in the decline of veracity in the external loop.

Comparing Figure 2 with the common Big Data distinguishing features shows that the value aspect is missing. The value cannot be pinpointed to any of the feedback loops. Rather, it is created as a result of them. In other words, value can be seen as an orthogonal dimension in relation to the ones presented above. Its minimums and maximums depend on the use case and may vary over time, e. g., a new robot automation working with feedback from the fast loop can bring a similar value, such as decisions made together with partners in the external loop.

4 Conclusion and Outlook

This paper presents a multi-feedback loop architecture controlling manufacturing steps, sub-processes, and processes. The main distinguishing features of the individual feedback loops are their time horizon and the degree of human involvement versus the degree of automation. The velocity, volume, variety, and veracity of the data handled in each feedback loop are additional characteristics that should be taken into account. While a high degree of automation has been a clear target for many decades, the vision of CIM from the 1980s has not been fully implemented to date. The co-existence of human workers and automated machinery in the individual feedback loops is still common practice today.

This work is an attempt to characterise and organise the multiple feedback loops maintaining a modern manufacturing process. The authors plan to investigate the feedback loops further by undertaking case studies at the industrial partners within the SemI40 project. With the input from the case studies, the authors plan to formalise the proposed feedback model further and investigate other aspects in collaboration between humans and automated manufacturing systems on manufacturing shop floors.

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