Perspective for equipment automation in process industries ⋆

Bei Sun * **Sirkka-Liisa Jämsä-Jounela** * **Yancho Todorov** *
Laurentz E. Olivier ** **Ian K. Craig** **

* *Department of Chemical and Metallurgical Engineering, School of Chemical Engineering, Aalto University, Espoo, Finland (sirkka-liisa.jamsa-jounela@aalto.fi)*
** *Department of Electrical, Electronic and Computer Engineering, University of Pretoria, Pretoria, South Africa (ian.craig@up.ac.za)*

Abstract: Advances in digital technologies are improving manufacturing systems dramatically. These advances, along with increased interconnectivity of devices, have launched the Industry 4.0 initiative that is concerned with how cyber physical systems and the internet of things can create adaptive, modularised, efficient, and reliable processing systems. This work presents a perspective on how equipment automation can contribute to this goal. Some of the main obstacles in the way of efficient and flexible operations are highlighted. How these may be overcome through equipment automation to form a cyber physical automation network is also presented. The effective integration of these methods can realize the vision of Industry 4.0 in the processing industry.

Keywords: process industry, equipment automation, smart equipment, Industry 4.0

1. INTRODUCTION

Industrial automation plays an important role in increasing production efficiency, reducing energy consumption, and optimizing production along business model requirements. Recently, driven by social demand and the rapid development of big data, cloud computing, and the internet of things (IoT) technologies, industrial automation systems are shifting from centralized systems to cyber-physical systems (CPS). The "blowout" of these enabling technologies facilitate technical innovation which is now recognized as the 4$^{\text{th}}$ industrial revolution (Jazdi (2014)). Many countries have embraced the upgrade of manufacturing systems as a national strategy to remain economically competitive. Examples include Germany's "Industrie 4.0" Platform (Germany Trade & Invest (2013)), USA's "Advanced Manufacturing Partnership (AMP)" (Anderson (2015)) and the "Industrial Internet Consortium (IIC)", Japan's "New Robot Strategy" (The Headquarters for Japan's Economic Revitualization (2015)) and "Industrial Value Chain Initiative", South Korea's "Manufacturing Industry Innovation 3.0 strategy" (Ministry of Trade, Industry and Energy (2014)), and the Chinese "Made in China 2025" initiative (The Sate Council (2015)) among others.

Driven by this global trend, novel concepts such as the Internet of Services (IoS) (Saldivar et al. (2015)), smart manufacturing (Gregor et al. (2015)), cloud manufacturing (Liu and Xu (2017)), social manufacturing (Jiang et al. (2016)) and their applications are emerging. Currently however, these applications are mainly found in the discrete manufacturing industries (Chen and Jin (2006)), e.g. the production of cars, electronic devices, and switches. There are only a few papers reported that study the application of Industry 4.0 in processing industries. This phenomenon is rooted in the inherent differences between discrete component manufacturing and the process industries (Taylor et al. (1981); Fransoo and Rutten (1994)). For discrete manufacturing, items (or parts) are produced either individually or in lots (Bitran and Morabito (1996)). In the process industries however (e.g. chemical, metallurgical, mineral processing, petrochemical) the content and form of the ingredients in raw materials are changed continuously by complex chemical and physical reactions, conducted in interconnected equipment networks (see Fig. 1). The control problems involved in process industries are often strongly nonlinear, with constraints, uncertainty, and multivariable control objectives. In the era of smart manufacturing, integrating the existing control methods with the enabling technologies of "Industry 4.0" enables highly efficient, adaptive, and flexible production (Chai (2016)).

Single pieces of equipment are the basic material processing components in process industries. The automation level of individual pieces of equipment can be upgraded to keep pace with the evolution of industrial automation technology. With this consideration, the future trends of equipment automation are investigated in this article. The main problems in achieving efficient and flexible operation are first discussed in Section 2. In Section 3, the role of equipment in a Cyber-Physical System is analysed. The scenarios of equipment automation are then described from different perspectives. Finally, in Section 4, an oper-

⋆ Sponsor and financial support acknowledgment goes here. Paper titles should be written in uppercase and lowercase letters, not all uppercase.

ational optimization framework based on distributed and networked smart agents is proposed and illustrated.

2. MAIN PROBLEMS IN ACHIEVING EFFICIENT AND FLEXIBLE OPERATION

In the process industries, raw materials are processed step by step until the final product is produced. The entire plant could be viewed as a network of equipment. The optimal operation of a single piece of equipment is determined from the value of its manipulated variables that are changed to fulfil certain functions. This can be seen as optimizing a certain performance index subject to imposed technical and process constraints. However, this optimization task is hampered by "information asymmetry". The individual piece of equipment has sufficient information about how it operates (e.g. its dynamics), but not much about the rest of the value chain.

2.1 Complex system dynamics

Equipment often has to contend with time-varying inputs and dynamics. In the plant, each piece of equipment interacts with upstream and downstream equipment through mass and energy transfers or recycles.

Inside reaction equipment, due to the heterogeneous nature of raw materials and processing conditions, there are not only main reactions but also side reactions whose dynamics and interaction mechanism with the controlled main reactions are not thoroughly known. In addition, changing material conditions or equipment/device malfunction can also cause undesirable fluctuations.

As an entity, an individual reactor is a system with multiple levels ranging from "molecule" through "particle" to "reactor". These levels have different temporal and spacial dimensions. The reactions happen on the molecular level, while the model for equipment control is on the reactor level. The gaps between different levels lead to uncertainties in the model used for control.

The same scenario exists for other pieces of equipment that are not reactors. A distillation column for example is often modelled as a single unit (Skogestad and Morari, 1988) with disregard for the comprising elements that define the working of the column. Modelling a distillation column as a series of individual trays can increase model accuracy, but the computational effort of using such a model is not always worth the additional accuracy. With the increase in computing power such models become more viable.

This argument is analogous for other equipment as well, such as pumps, compressors, furnaces, and heat exchangers. All of these equipment can be modelled on a more fundamental level, with some model parameters determined from operating data. Modelling in this fashion is called grey-box modelling, and generally leads to good accuracy while maintaining a degree of flexibility.

2.2 Limited measurements

As a component in the plant-wide material flow, the physical and chemical properties of the material inside the equipment (e.g. the concentration of reagent in a reactor) are usually defined as the system states, which are used in state feedback control. However, in practice, some state values remain unknown due to the high price of sensors (when they exist) and a lack of appropriate soft sensors (Ali et al. (2015)). An observer is then required to reconstruct the states using available measurements and the system model.

2.3 Rigid production mode

According to the Purdue Enterprise Reference Architecture (PERA) (see Fig. 2), equipment control is situated on level 1 of the automation hierarchy pyramid. The lateral flow of equipment information is often blocked. Equipment operate in isolation without any interface to vertical or horizontal communication with other equipment and systems, except that the operating point of the equipment may be set by a higher level decision maker. The material flow along the equipment is also fixed due to a lack of flexibility.

From the above, it is evident that improving the availability of knowledge and information could enable the optimal operation of equipment in an efficient way. And on the other hand, unblocking the flow of knowledge and information could enable more flexible production.

3. TOWARDS SMART EQUIPMENT-SCENARIOS OF EQUIPMENT AUTOMATION

Feedback plays a key role in control theory. In a CPS, the integration is essential in various aspects, e.g. horizontal integration through value networks, vertical integration through networked manufacturing systems, and end-to-end digital integration of engineering across the entire value chain. For a single piece of equipment, integration is also crucial to increase its ability. In this section, the role of equipment in a Cyber-Physical System is first discussed and then some scenarios of equipment automation in this context are presented.

3.1 Role of equipment in a Cyber-Physical System

In a CPS, the real, the virtual, and the digital factory are integrated. The manufacturing value chain in the physical world can be integrated with its virtual copy, or digital twin, through CPS and IoT (Internet of Things), and then be seamlessly integrated with IoS. The design, development, use, and recycling phase and the whole life-cycle of products, services, and processes are considered within the global context of product life-cycle management. Traditional products may then be produced in a more efficient way. The factory can also instantly and flexibly respond to changing material conditions, various customer demands, disruptions, and failures. New types of products and services may also result when using a CPS approach.

In order to realize this flexible and highly efficient means of production, the structure of the automation system will have to shift from the hierarchical pyramid of Fig. 2 to a non-hierarchical structure such as that shown in Fig. 3. Such a non hierarchical structure could enable many advances on shop floor level (Cardin et al. (2016)). The

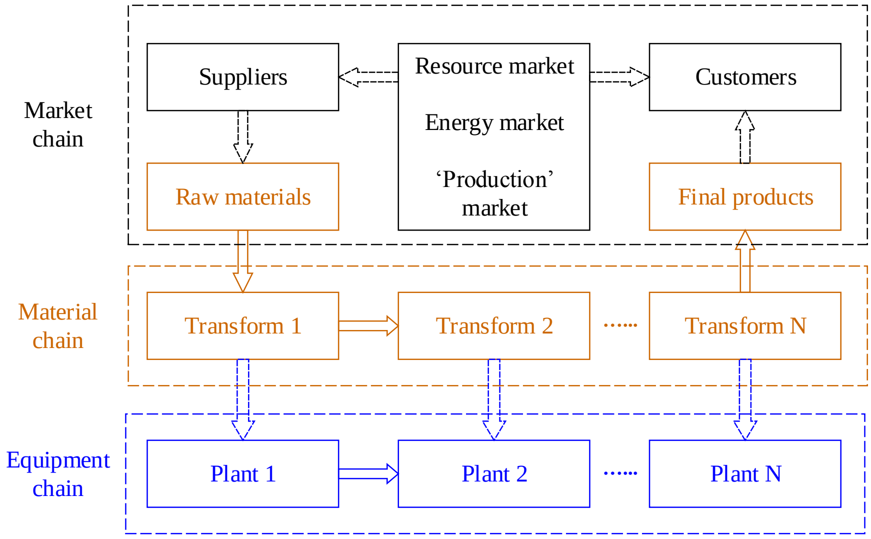

Fig. 1. Market chain, material chain, and equipment chain in process industries.

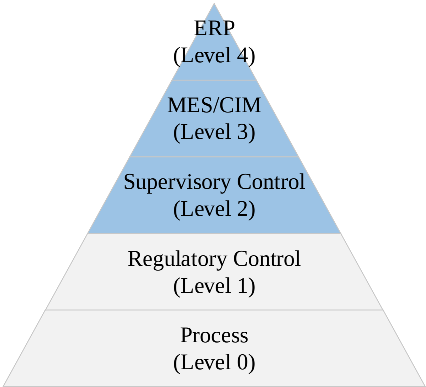

Fig. 2. Traditional pyramid structure in plant automation.

automation functions are decentralized, and the "intelligence" of a centralized system is moved into individual pieces of equipment. In this CPS structure an individual piece of equipment can be considered as a cyber-physical component. Such equipment is autonomous and can make decisions by itself and serves as a link between physical material and knowledge/information. It automatically collects, analyses, and utilizes the data to manage the information flow and extract knowledge from the data and information, in order to make sense of the process and to optimize the process operation. The equipment is connected in a non-hierarchical reconfigurable manufacturing network context which enables self-organization as well as plug and play. The data, information, and knowledge are shared locally and globally through the use of wireless sensor nodes and networks. Such smart equipment can participate actively and collaboratively to support the entire manufacturing value chain in a global context.

Practically then each piece of equipment is well aware of its own states and outputs. This information is passed downstream along the value chain such that subsequent pieces of equipment know what to expect regarding inputs and disturbances. Information about downstream bottlenecks and equipment failures should be transmitted upstream such that material routings can be adjusted dynamically.

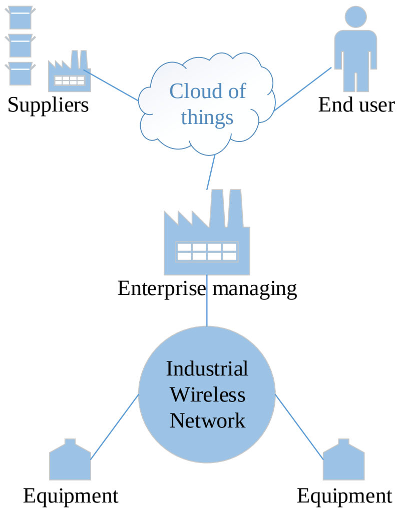

Fig. 3. Non-hierarchical manufacturing network structure of CPS.

Each piece of equipment has a corresponding model in the digital twin, and this model is used for local state estimation, fault detection and isolation (FDI), and local control.

3.2 Equipment automation dimensions

The operational dimension

(i) Integration of advanced control, fault diagnosis, self-recovery, and big-data analytics:
There is a large body of literature on advanced control, fault diagnosis, self-recovery, and big-data analytics. These fields contribute to equipment automation from different points of view, but their integration has however not been studied much. Advanced control methods are designed with specific emphasis and could be divided into different types, e.g. model-based control, intelligent control, adaptive control, discrete event techniques, event-triggered, and self-triggered control. By itself, any single control method

is incapable of handling the complex system dynamics of an entire processing plant. Considering fault diagnosis in the traditional automation pyramid, it is usually implemented at the supervisory level which is higher than the control systems level. It shares the same measured variables but may have competing objectives with optimizing control (Du et al. (2016)).

Machine learning algorithms and big data analytics are able to improve the efficiency of industrial processes and to support predictive maintenance. Therefore, the integration of advanced control, fault diagnosis, self-recovery, and big-data analytics increases information utilization and enables a better understanding of equipment behaviour. Thus the implementation of control, fault diagnosis, and data analytics in a unified framework could guarantee production safety, increase production efficiency, and ensure optimal economic performance.

(ii) Intelligent perception:
Equipment is operated in a changing environment with time-varying inlet and material conditions. Consciously being aware of the status of the material flow is the foundation of an agile production system that can adapt rapidly to changing material conditions. The material conditions inside equipment can be estimated using a state observer. However, many existing observers rely on accurate process models, which are usually unavailable, especially in chemical and metallurgical processes. In order to circumvent the modelling difficulty, artificial intelligence has been introduced in the observer design step (Ali et al. (2015)). Unfortunately, the AI-based observers are limited in terms of robustness and ensuring convergence. Thus, integrating AI-based observers with the strictly convergent observers to reconstruct system states in a rigorous and intelligent manner will likely be a future trend in state estimation.

(iii) Value-chain optimization:
Given that individual pieces of equipment can be controlled sufficiently and that proper integration of advanced control, FDI, and big-data analytics has occurred, the global value-chain optimum still needs to be defined in order to ensure that all equipment contribute to achieving this optimum.

The global value chain optimum in a continuous processing system is often defined by the product values, cost of feedstock, and cost of processing. Product values define which product grades should preferentially be produced. Cost of feedstock defines which supplies should preferentially be used. Cost of processing encapsulates energy costs and conversion costs (such as catalyst or utilities). A distributed optimization scheme (such as distributed MPC (Camponogara et al., 2002)) can then be used to attain the value chain optimum. Separation equipment may focus on the product yields in as much as they affect downstream routings and final product deliveries. Pumps may only be concerned with operating close to the efficiency point while delivering the required discharge flow.

Another consideration for value-chain optimization is how the process should adapt in the presence of faults in the system (as is considered in Olivier and Craig (2017)). Some faults are not very detrimental to process operations, while other may necessarily to process stoppages. Plant economic performance should also be considered with faults present and, as Olivier and Craig (2017) shows, for some faults it may be more economical to shut the plant down, fix the fault(s), and start up again than simply operating with faults (even they do not cause process stoppages).

The virtual dimension

(i) Digitalization and virtualization:
Digitalization and virtualization project the physical equipment into a virtual equipment "data space" to create a cyber or digital twin of the equipment which is able to analyse the production data, extract knowledge, perform control and fault diagnosis, while interacting with other components in the entire cloud manufacturing system.

(ii) Knowledge automation:
Equipment constitute visible physical assets of a plant, while knowledge is recognized as a valuable but invisible asset of an enterprise (Da Xu (2011); Gui et al. (2016)). Knowledge plays a key role in enterprise management and plant production. In modern industry, the automation of machines has liberated operators from the physical work with high labour intensity. However, decision making, planning, and dispatching still rely on the knowledge of human beings. Knowledge automation will enable equipment to learn from the production data automatically, which involves:

- knowledge discovery: There are various sources of knowledge in industry, including data knowledge, mechanism knowledge and experience knowledge. Such knowledge has different manifestations, various magnitudes, and multiple time scales. Knowledge discovery aims to extract the information contained in large amounts of production data into useful knowledge that forms a basic knowledge library.
- knowledge utilization and creation: This process involves simulating the thought processes of human beings to produce new knowledge elements through data correlation and inference or through the restructuring of existing knowledge elements.

The communication dimension

(i) Remote monitoring and operation:
In the wireless industrial internet, every single piece of equipment has an assigned IP address to communicate with other members of the CPS. Users can access and change the equipment conditions via the cloud or the internal wireless industrial internet. Wireless communication also provides flexibility in plant layout and reduces the planning effort in that cabling is no longer required.

(ii) Information security:
Equipment production data are usually confidential. Only authorized users can access a certain piece of equipment within a plant, and such access should be controlled.

Smart equipment design and production

(i) Integrated equipment design:
Traditionally, the control system is designed only after the plant is built. This type of design is not optimal as it possesses a smaller degree of freedom compared to when controller design is integrated with equipment design. In the integrated equipment design, the control, communication, and the machinery will be designed simultaneously which can lead to significant economic benefits and improved dynamic performance during plant operation.

(ii) Customized and modularized equipment production:
In order to realize plug and play in a reconfigurable manufacturing network, the production standards of equipment must agree, including communication and hardware interfaces. The components of equipment can be modularized. The users of the equipment will be involved in the equipment design to enable customization. The future PLC will become the interface between physical and cyber equipment. As such it can serve as a complex service object in the manufacturing value chain, which will interpret the service requests to the equipment level. On the other hand, it will possess high computational power, low energy consumption and self-sufficient functionality.

4. DISTRIBUTED AND NETWORKED SMART MANUFACTURING SYSTEMS

The smart equipment with wireless communication will form a distributed, networked, smart manufacturing system that is efficient in its use of resources, highly resilient to disturbances, and adaptable to changes in the environment in which it exists. In a distributed networked smart manufacturing system, each piece of equipment could be viewed as an agent with autonomy and coordinating abilities. An example of such a system is shown in Fig. 4.

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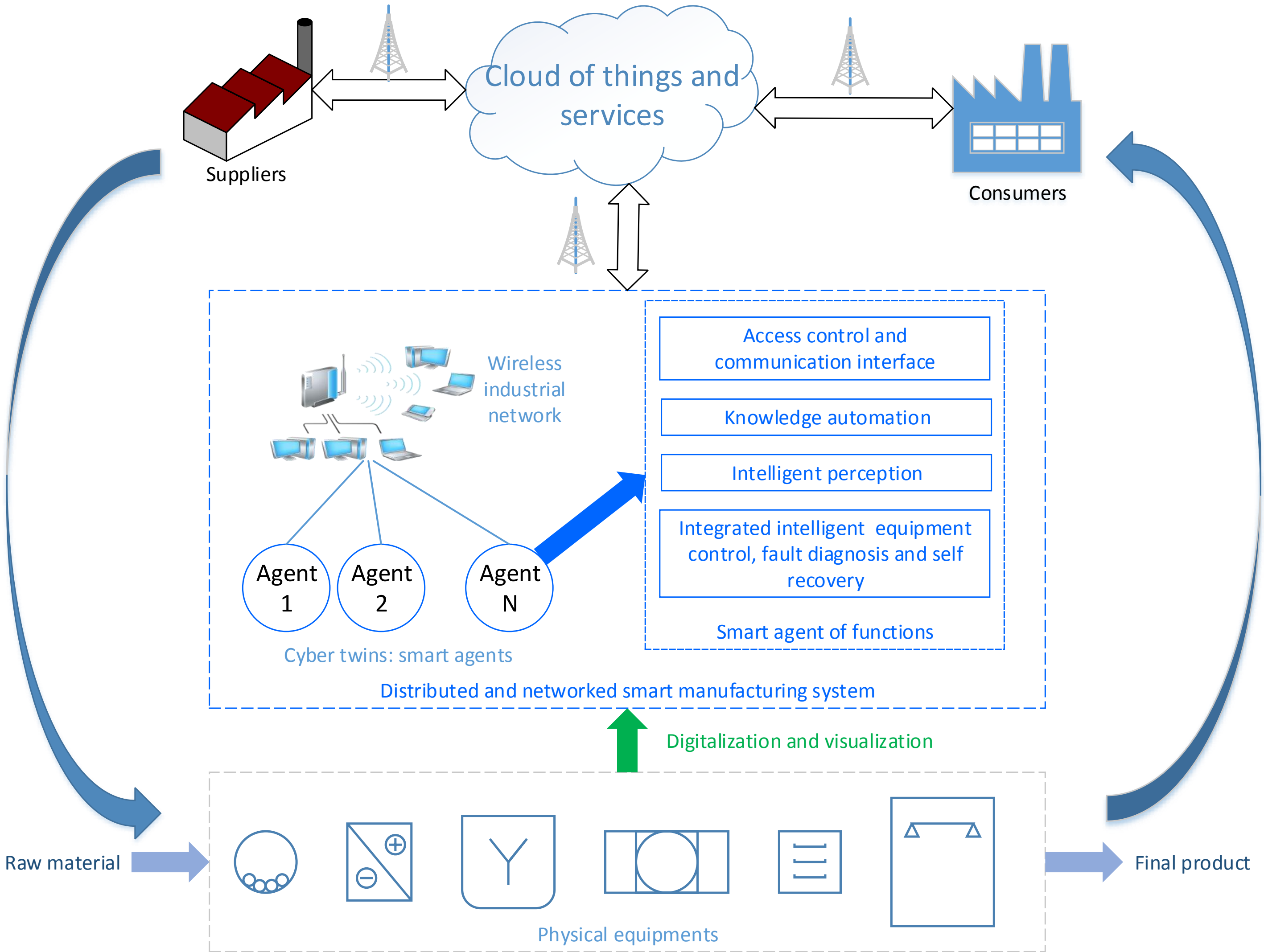

Fig. 4. Distibuted networked smart manufacturing system