
This is an electronic reprint of the original article.
This reprint may differ from the original in pagination and typographic detail.

Sun, Bei; Jämsä-Jounela, Sirkka-Liisa; Todorov, Yancho; Olivier, Laurentz; Craig, Ian
Perspective for equipment automation in process industries

Published in:
IFAC-PapersOnLine

DOI:
[10.1016/j.ifacol.2017.12.012](https://doi.org/10.1016/j.ifacol.2017.12.012)

Published: 01/01/2017

Document Version
Publisher's PDF, also known as Version of record

Published under the following license:
CC BY-NC

Please cite the original version:
Sun, B., Jämsä-Jounela, S-L., Todorov, Y., Olivier, L., & Craig, I. (2017). Perspective for equipment automation in process industries. *IFAC-PapersOnLine*, 50(2), 65-70. <https://doi.org/10.1016/j.ifacol.2017.12.012>

This material is protected by copyright and other intellectual property rights, and duplication or sale of all or part of any of the repository collections is not permitted, except that material may be duplicated by you for your research use or educational purposes in electronic or print form. You must obtain permission for any other use. Electronic or print copies may not be offered, whether for sale or otherwise to anyone who is not an authorised user.

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)

^{***} School of Information Science and Engineering, Central South University, Changsha, China

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.

© 2017, IFAC (International Federation of Automatic Control) Hosting by Elsevier Ltd. All rights reserved.

Keywords: process industry, equipment automation, smart equipment, Industry 4.0, Industrial Internet of Things

1. INTRODUCTION

Industrial automation plays an important role in increasing production efficiency, reducing energy consumption, and optimizing the production mode along business model requirements. Since this decade, driven by social demand and the rapid development of ICT technologies, e.g., big data, machine learning, cloud computing, and the internet of things (IoT), industrial automation systems are shifting from centralized systems to cyber-physical systems (CPS) (Jazdi, 2014). This wave of technical innovation is now recognized as the 4th industrial revolution.

Many countries have embraced the upgrade of manufacturing industry as a national strategy to remain economically competitive. Examples include Germany's "Industrie 4.0" Platform (Bunse et al., 2014), USA's "Industrial Internet of Things (IIoT)", Japan's "New Robot Strategy" (The Headquarters for Japan's Economic Revitalization, 2015) and "Industrial Value Chain Initiative", South Korea's "Manufacturing Industry Innovation 3.0 strategy" (Ministry of Trade, Industry and Energy, 2014), and China's "Made in China 2025" initiative (The State Council, 2015).

^{*} This work is based on research supported by the project (No. 296432), Towards sustainable mineral processing via plantwide eMPC, Mineral Resources and Material Substitution-MISU, 2014-2019 Int. call for joint projects in mineral resources research, South Africa and Academy of Finland, project 5G meets Industrial Internet financed by Technology Industries (No. 3102144), the National Natural Science Foundation of China project (No. 61603418), the 111 Project (B17048), the National Research Foundation of South Africa (IRC grant number 103666).

These strategies have diverse application areas and different emphases. IIoT is an industrial adaptation of IoT, in response to a consumer-facing trend on enabling the internet technologies across industries, while Industrie 4.0 is focused on proposing new business models related to manufacturing, in order to ensure the competitiveness of the manufacturing industry on the dynamic global market. Driven by this global trend, novel concepts and standards, such as the Decentralized Intelligence for Modular Systems (DIMA) (WAGO, 2015), NAMUR Module Type Package (MTP) (Obst et al., 2015), BASF 4.0 (Klinger, 2017), IIRA (Lin et al., 2015), Internet of Services (IoS) (Saldivar et al., 2015), cloud manufacturing (Liu and Xu, 2017), social manufacturing (Jiang et al., 2016), to name a few, and their applications are emerging in both discrete and process industries.

This phenomenon is rooted in the inherent differences between discrete industries and process industries (Taylor et al., 1981; Fransoo and Rutten, 1994). In discrete industries (e.g. automobile industry, electronic industry), items (or parts) are produced either individually or in lots (Bitran and Morabito, 1996). The operations involved are mainly producing and assembling of parts or components. However, in the process industries (e.g. chemical, metallurgical, petrochemical), the concentrations of ingredients and the composition of materials being processed are changed continuously by complex chemical and physical reactions conducted under time-varying feeding and working conditions (Chai, 2016). As a result, the control problems involved in process industries are often strongly

nonlinear with mixed constraints, complex couplings, competing objectives and uncertainties on various levels. In addition, in some cases, the hostile production conditions (e.g. high temperature, strong acidity) would obstruct the use and maintenance of detecting instruments. With limited knowledge of system dynamics and restricted availability of KPIs (Key Performance Index), the operators encounter the 'information asymmetry' situation in which the decisions are made under uncertainty and it is thus hard to achieve global optimal.

In the era of smart manufacturing, the emerging ICT technologies provide tools and potential solutions to lift the 'information asymmetry' situation by: i). extracting useful information from big industrial data with various sources ranging from sensors to international market, ii). extracting knowledge from information and infuse intelligence into automation system, iii). projecting the physical process into a virtual data space to enable the communication and cooperation among components from different levels. Hence, integrate existing control methods with the emerging ICT technologies to increase the information utilization efficiency and eliminate the aforementioned obstacles is a practical solution for the upgrading of process industries.

In the process industries, an entire plant could be viewed as a network of equipments which are the basic material processing components (see Fig. 1). The automation level of individual pieces of equipment should keep pace with the entire plant (Jämsä-Jounela, 2007; Li, 2016). With this consideration, this article studies: i). how the ICT technologies together with advanced control theory could be used to improve the equipment automation level, or in other words, make the equipment 'smart', ii). how the smart equipment would change the plant-wide control. The main challenges in the development of smart equipment are first discussed in Section 2. Aiming to overcome these challenges, the integration of existing control methods and ICT technologies, and the scientific problems in the integration are discussed in Section 3. The scenario of equipment automation is described from different perspectives. In Section 4, the role of smart equipment in a cyber-physical plant is analysed. A new operational optimization framework based on distributed and networked smart agents is proposed and illustrated. Section 5 concludes this study.

2. CHALLENGES IN THE DEVELOPMENT OF SMART EQUIPMENT

For a single piece of equipment, the aim of optimal operation is to fulfill certain functions in a most efficient way by choosing the best combination of manipulated variables. From the plantwide viewpoint, the operation involves production planning and coordination among equipments. Both cases can be regarded as optimizing a certain performance index subject to imposed technical, process and economical constraints. However, this optimization task is hampered by the "information asymmetry" mentioned in the introduction, which can be explained in detail from following aspects.

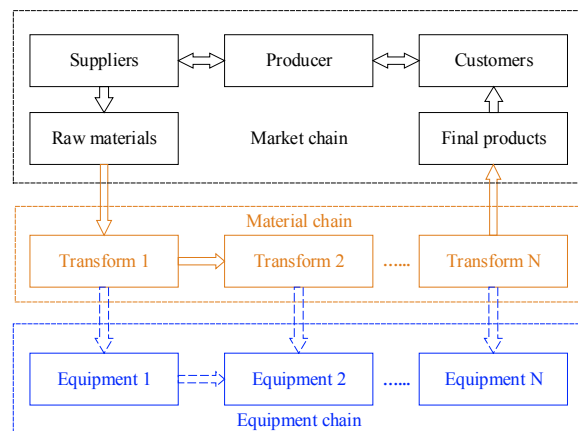


Fig. 1. Market chain, material chain and equipment chain in process industries

2.1 Complex system dynamics

As a component of a plant, each piece of equipment interacts with upstream and downstream equipment through mass and energy transfers or recycles. So equipment often has to contend with time-varying inlet conditions. In addition, due to the heterogeneous nature of raw materials, inside an equipment, there are not only main reactions but also side reactions whose dynamics and interaction mechanism with the controlled main reactions are not thoroughly known. Changing feeding conditions or equipment/device malfunction can also cause undesirable fluctuations.

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

The intricate interactions and the gaps between different levels lead to the complex dynamics of a single equipment. Modelling of an equipment is to determine adequate model structure and identify the model parameters. A comprehensive and precise model is usually costly to obtain. In practice, the equipment model is a compromise between feasibility and accuracy. 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, where the model structure is defined by the physical equipment, and the parameters based on operating data, is called grey-box modelling, and generally leads to good accuracy while maintaining a degree of flexibility.

2.2 Limited measurements

As a connection point in the plant-wide material flow, the physical and chemical properties of the material inside an equipment (e.g. the concentration of reagent in a reactor) are usually defined as the system states, which are essential in state feedback control. However, in practice, online-detection of all the state variables are not always available due to the high cost in the purchasing and maintenance of detecting instruments (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 operating points of an equipments are set by a higher level decision maker. However, the lateral information flow between equipments is often blocked. The individual piece of equipment has sufficient information about how it operates (e.g. its working conditions), but not much about the rest of the value chain. Unblocking the information flow and allocating more intelligence on the floor level would increase the flexibility of production. Examples include the open architecture driven by Exxon to enable vertical communication with other equipment or horizontal communication in order to move advanced process control from level 3 to level 1-2.

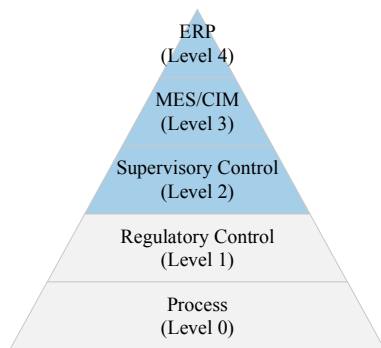


Fig. 2. Traditional pyramid structure of industrial automation system

From the above, it is evident that extracting more knowledge/information from production data could increase the understanding of system dynamics and support the optimal operation of equipment in an efficient way.

3. TOWARDS SMART EQUIPMENT-SCENARIO OF EQUIPMENT AUTOMATION

In a CPS, the integration is essential in various aspects, e.g. integration of value networks (Wang et al., 2016), integration of models and tools (Li, 2011). For a single piece of equipment, integration is also crucial to increase its ability and intelligence. In this section, how the ICT technologies and advanced control theories could be integrated to make the equipment 'smart' is discussed from different aspects. The scenario of equipment automation in this context is presented.

3.1 The operational dimension

In order to overcome the 'information asymmetry' problem, a feasible approach is to increase the information utilization rate by integrating different control/estimation approaches which use different sources of data and provide supporting information from different aspects. In addition, knowledge automation, which could be used to extract knowledge from information, will enable an equipment to generate intelligence automatically.

- (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 (Dotoli et al., 2017). 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).

By learning from production data, machine learning algorithms and big data analytics are able to improve the efficiency of advanced control and to support predictive maintenance (Haverkort and Zimmermann, 2017). Therefore, the integration of advanced control, fault diagnosis, self-recovery, and big-data analytics increases information utilization efficiency 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 and flexibility, increase production efficiency, and ensure optimal economic performance.

- (ii) Intelligent perception:

Equipment is operated in a changing environment with time-varying feeding 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) Knowledge automation:

Equipment constitute visible physical assets of a plant, while knowledge is recognized as a valuable but invisible asset of an enterprise (Li, 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.

In addition, knowledge standardization and sharing, which transfer the knowledge generated by one equipment or in one plant to another, is another important problem to be addressed.

(iv) 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 lead 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 if they do not cause process stoppages).

3.2 The communication 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) Remote monitoring and operation:

Wireless communication provides extra flexibility by reducing the planning effort in cabling. In the wireless industrial internet, every single piece of equipment has an assigned IP address as an identity to communicate with other members of the CPS. Users can access and change the equipment conditions via the cloud or the internal industrial wireless internet. OPC UA (Unified Architecture) and 5G technologies with features like ultra-dense Hetnets, 3D/Massive MIMO, Non-Orthogonal Multiple Access, would support the real-time and standard communication among suppliers, customers and producers in the cloud.

(iii) Information security and plant safety:

Equipment production data are usually confidential. In order to avoid hacker attack, only authorized users can access a certain piece of equipment within a plant, and such access should be controlled.

3.3 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 lower degree of freedom compared to the case in which controller design is integrated with equipment design. In the latter case, the control, communication, and the machinery will be designed simultaneously which can lead to better operational performance during production.

(ii) Customized and modularized equipment production:

In order to realize plug and play in a reconfigurable manufacturing network, the production standards of equipment must be unified, including communication protocols and hardware interfaces. The components of equipment can be modularized. The information provided by components like sensors could be customized. The users of the equipment will be involved in the equipment design to enable customization. More advanced PLC with higher computation power and energy efficiency will serve as the interface between physical and cyber equipment. Many control-related functions will be integrated and introduced into the PLC. As such it will possess self-sufficient functionality and act as a complex service object in the manufacturing value chain, which will interpret the service requests to the equipment level (Zuehlke, 2010).

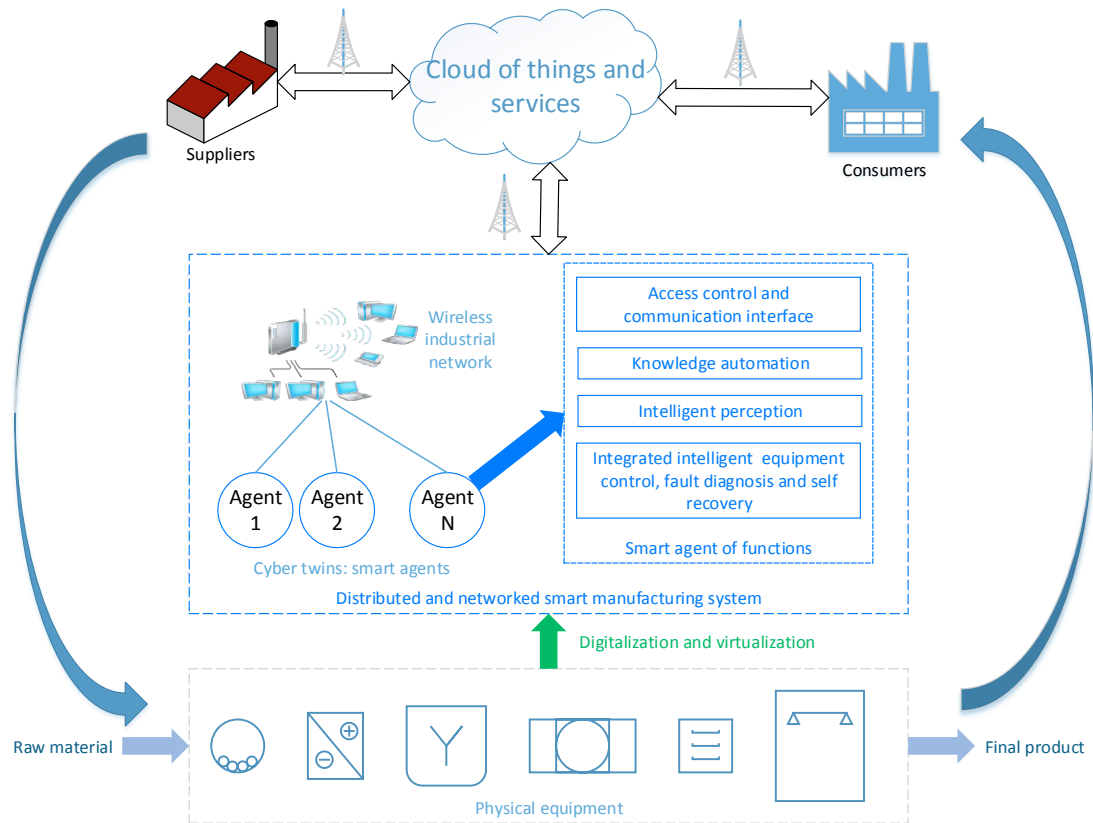


Fig. 3. Distributed networked smart manufacturing system

4. DISTRIBUTED NETWORK OF SMART EQUIPMENT AGENTS

In a CPS, the physical plant is integrated with its virtual copy, or digital twin which is connected with suppliers, consumers and other enterprises through IoT (Internet of Things) or IoS. The design, production, recycling and service are considered within the global context of product life-cycle management. Products may then be produced in a more efficient way. The factory can instantly and flexibly respond to changing material conditions, various customer demands, disturbances, 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, from the perspective of operational optimization, the structure of the automation system will shift from the hierarchical pyramid of Fig. 2 to a non-hierarchical structure such as that shown in Fig. 4. Such a non hierarchical structure could enable many advances on shop floor level (Cardin et al., 2016). The 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, i.e., an agent. 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 production 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 con-

nected in a non-hierarchical reconfigurable manufacturing network context which would enable 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.

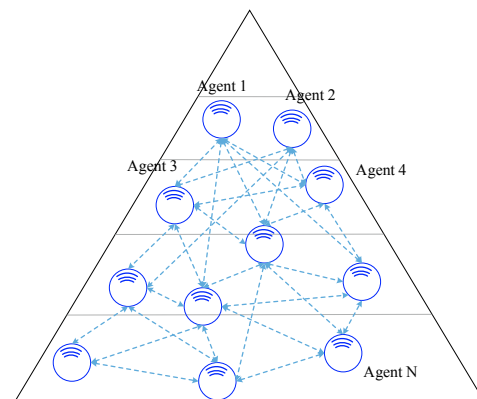


Fig. 4. Non-hierarchical manufacturing network structure of CPS.

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 flow can be adjusted dynamically. Each piece of equipment has a corresponding model in the digi-

tal twin, and this model is used for local state estimation, fault detection and isolation (FDI), and local control.

5. CONCLUSION

The advances in ICT technologies bring new opportunities for the upgrading of equipment automation. In a smart factory, each piece of equipment will be no longer considered only as a physical component. It will become smart, and could be viewed as an agent with autonomy and coordinating abilities. The smart equipment with wireless communication will form a distributed, networked, smart manufacturing system that is economical efficient, intelligent, robust to uncertainties and external disturbances, flexible and adaptable to changes in the global value chain. There are however challenges, which include both scientific problems and practical issues, to overcome before the scenario can become a reality.

REFERENCES

- Ali, J.M., Hoang, N.H., Hussain, M.A., and Dochain, D. (2015). Review and classification of recent observers applied in chemical process systems. *Computers & Chemical Engineering*, 76, 27–41.
- Bitran, G.R. and Morabito, R. (1996). State-of-the-art survey: Open queueing networks: Optimization and performance evaluation models for discrete manufacturing systems. *Production and Operations Management*, 5(2), 163–193.
- Bunse, B., Kagermann, H., and Wahlster, W. (2014). Industry 4.0: Smart manufacturing for the future. *Germany Trade and Invest*.
- Camponogara, E., Jia, D., Krogh, B., and Talukdar, S. (2002). Distributed model predictive control. *IEEE Control Systems*, 22, 44 – 52.
- Cardin, O., Ounnar, F., Thomas, A., and Trentesaux, D. (2016). Future industrial systems: Best practices of the intelligent manufacturing & services systems (IMS 2) French research group. *IEEE Transactions on Industrial Informatics*, 13, 704 – 713.
- Chai, T. (2016). Industrial process control systems: research status and development direction. *SCIENTIA SINICA Informationis*, 46(8), 1003–1015.
- Dotoli, M., Fay, A., Miśkiewicz, M., and Seatzu, C. (2017). Advanced control in factory automation: a survey. *International Journal of Production Research*, 55(5), 1243–1259.
- Du, Y., Budman, H., and Duever, T.A. (2016). Integration of fault diagnosis and control based on a trade-off between fault detectability and closed loop performance. *Journal of Process Control*, 38, 42–53.
- Fransoo, J.C. and Rutten, W.G. (1994). A typology of production control situations in process industries. *International Journal of Operations & Production Management*, 14(12), 47–57.
- Gui, W., Chen, X., Yang, C., and Xie, Y. (2016). Knowledge automation and its industrial application. *SCIENTIA SINICA Informationis*, 46(8), 1016–1034.
- Haverkort, B.R. and Zimmermann, A. (2017). Smart industry: How ict will change the game! *IEEE Internet Computing*, 21(1), 8–10.
- Jämsä-Jounela, S.L. (2007). Future trends in process automation. *Annual Reviews in Control*, 31(2), 211–220.
- Jazdi, N. (2014). Cyber physical systems in the context of industry 4.0. In *Automation, Quality and Testing, Robotics, 2014 IEEE International Conference on*, 1–4. IEEE.
- Jiang, P., Ding, K., and Leng, J. (2016). Towards a cyber-physical-social-connected and service-oriented manufacturing paradigm: Social manufacturing. *Manufacturing Letters*, 7, 15–21.
- Klinger, A. (2017). The contribution of iot in process manufacturing. https://internetofbusiness.com/wp-content/uploads/2017/02/Andreas-Klinger_BASF_The-contribution-of-IoT-in-process-manufacturing.pdf. Accessed Jun 21, 2017.
- Li, D.X. (2011). Enterprise systems: state-of-the-art and future trends. *IEEE Transactions on Industrial Informatics*, 7(4), 630–640.
- Li, D. (2016). Perspective for smart factory in petrochemical industry. *Computers & Chemical Engineering*, 91, 136–148.
- Lin, S.W., Miller, B., Durand, J., Joshi, R., Didier, P., Chigani, A., Torenbeek, R., Duggal, D., Martin, R., Bleakley, G., et al. (2015). Industrial internet reference architecture. *Industrial Internet Consortium (IIC), Tech. Rep.*
- Liu, Y. and Xu, X. (2017). Industry 4.0 and cloud manufacturing: A comparative analysis. *Journal of Manufacturing Science and Engineering*, 139(3), 034701.
- Ministry of Trade, Industry and Energy (2014). The industrial innovation movement 3.0 for manufacturing industry for realization of creative economy.
- Obst, M., Holm, T., Urbas, L., Fay, A., Kreft, S., Hепен, U., and Albers, T. (2015). Semantic description of process modules. In *Emerging Technologies & Factory Automation (ETFA), 2015 IEEE 20th Conference on*, 1–8. IEEE.
- Olivier, L.E. and Craig, I.K. (2017). Should i shut down my processing plant? - An analysis in the presence of faults. *Journal of Process Control*.
- Saldivar, A.A.F., Li, Y., Chen, W.n., Zhan, Z.h., Zhang, J., and Chen, L.Y. (2015). Industry 4.0 with cyber-physical integration: A design and manufacture perspective. In *21st International Conference on Automation and Computing (ICAC)*, 1–6. IEEE.
- Skogestad, S. and Morari, M. (1988). Understanding the dynamic behavior of distillation columns. *Industrial Engineering Chemical Research*, 27, 1848 – 1862.
- Taylor, S.G., Seward, S.M., and Bolander, S.F. (1981). Why the process industries are different. *Production and Inventory Management Journal*, 22(4), 9–24.
- The Headquarters for Japan’s Economic Revitalization (2015). New robot strategy.
- The Sate Council (2015). Made in China 2025.
- WAGO (2015). A revolutionary automation solution from wago for the process industry. <http://www.automationinside.com/2015/01/a-revolutionary-automation-solution.html>. Accessed Jun 21, 2017.
- Wang, S., Wan, J., Li, D., and Zhang, C. (2016). Implementing smart factory of industrie 4.0: an outlook. *International Journal of Distributed Sensor Networks*.
- Zuehlke, D. (2010). Smartfactory towards a factory-of-things. *Annual Reviews in Control*, 34(1), 129–138.