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The Impact of Digitalization on the Future of Control and Operations

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Abstract

The notion of Internet of Things (IoT), as well as related topics such as Cyber-Physical Systems, Industrie 4.0 and Smart Manufacturing are currently attracting a lot of attention within the process and manufacturing industries. Clearly, IoT offers many potential applications for automation, ranging from engineering installation of new plants to production management and more intelligent maintenance schemes including novel sensor technologies. The focus of this paper is, however, on the control and operations. Most likely IoT leads to new system architectures where open standards play a significant role. Through better connectivity, information will be much more easily available, which could result in that previously isolated functions will become more closely integrated. Here modeling at the right level of fidelity will be absolutely key. It can be expected that the importance of optimization will increase and this paper discusses some aspects related to the opportunities, challenges and changes triggered by IoT.

Keywords: Digitalization, Control, Operations, Optimization, Scheduling, Process Automation.

1. Introduction

The control and operations of process plants has undergone significant developments compared to the early analogue regulatory schemes. Computer based supervisory control was first tried already in the late 1950s. With the advent of the microprocessor the first distributed control systems (DCS) were introduced in the 1970s. This is sometimes referred to as the first digital revolution. Later, increased computational power as well as development of better optimization solvers have enabled advances also for the upper layers of the automation hierarchy.

However, a typical process industry company has separate departments for different functions such as plant operations, production planning, energy planning, supply chain optimization and maintenance management. Furthermore separate computer tools are traditionally deployed for these functions, which are often geographically distributed across a site or they can even be in different locations.

With the improved connectivity and dramatically increased access to computational power the so-called Internet of Things (IoT) shows promise of an increased integration of the control and operations in the process industry. The purpose of this paper is to discuss, more in detail, some of the currently on-going developments and to humbly try

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to predict some future changes that may occur as a result of this second digital revolution of industry. It will be shown that it is valuable to have access to supporting tools that ensure correct, agile and more efficient reactions to changes and that open the possibility for optimization also within a complex and frequently changing environment.

2. Business Challenges for Automation

Before focusing on technology it is important to consider that at the end of the day the aim is to obtain tangible economic benefits for the industry. Already 2005 during the work towards a Strategic Research Agenda for the EU technology platform for embedded systems – ARTEMIS – the first author together with a former ABB colleague, Nils Leffler, formulated two Grand Challenges for Automation:

- The sustainable 100 % available plant
- To engineer systems 10 times of today's complexity with 10% of today's effort

The first challenge stresses that the highest priority for all process and manufacturing industry is that the production is in fact running. The 100 % availability captures the vision that in the future there will be only planned maintenance stops. It can of course be debated whether this vision is realistic or even desirable, but as a vision it is hard to aim for anything less. In practice, one needs to find the right balance between maintenance cost and risk. Much of this relates rather to topics like condition monitoring and predictive maintenance, which are at the heart of the industrial digitalization but beyond the scope of this paper. Instead, what will be discussed below is embedded in the one word "sustainable", which then refers to topics like productivity, as well as, resource and energy efficiency.

The second challenge is primarily that of the automation suppliers. Regardless of the level of automation there needs to be continuous improvement in the time it takes to configure and commission new systems, solutions and products. We will come back to this challenge several times in the remainder of this paper.

The scope of the two Grand Challenges formulated 12 years ago is within a particular plant and its automation system. Both challenges are still relevant and the technologies of the industrial digitalization help to address them in several respects. However, along the second digital revolution in industry the scope for automation is increasing from single plants to networks of plants, or even value creation networks composed of value creation nodes of various types across an entire enterprise. In particular in the process industries, where several plants are interconnected by networks of utilities and intermediates, a more holistic automation approach might remove artificial constraints and unlock additional optimization potential.

Consequently, in 2016 a European Research and Innovation Agenda on Cyber-Physical Systems of Systems was proposed by three working groups (Engell and Sonntag, 2016). One core challenge with relevance to the nine considered technology sectors including the process industry is "distributed, reliable and efficient management of cyber-physical systems of systems". It is based on the observation that cyber-physical systems of systems cannot be managed and operated reliably and efficiently by centralized management and control, but require novel distributed management and control methodologies that can deal with partially autonomous systems with human interaction and frequently changing system structures. Particular research and innovation priorities from the field of process control and operations cover

- distributed robust system-wide optimization methods,
- system operation methods combining data-driven and model-driven approaches and
- integration of control, scheduling, planning and demand-side management for industrial production systems.

All of them are touched in the sequel of this paper.

3. Industrial digitalization

The last 10-15 years have seen a phenomenal development: the internet and later smart phone apps have changed almost every facet of our daily life. They have altered the way how we book travel, do our banking, watch TV, keep in contact with our friends etc. The drastic changes to the consumer market have, however, not yet fully reached the business to business market. Digitalization of industry began already in the 1970s when microprocessor controllers and distributed control systems were first introduced. In parallel the deployment of information technology (IT) in general and particularly the utilization of internet have increased especially from the 1990s, but the main functionalities and information have so far been separated from the control room by a firewall and the data flow has been primarily one-directional. What is now often referred to as "Digitalization" could also be called the second digital revolution. It will lead to a much closer integration of operational technology (OT) and IT. For a discussion of the economic potential of the Industrial Internet see Evans and Annunziata (2012).

Hence, similar to the way our daily life as private consumers has been transformed, the current industrialization digitalization will have a profound impact on every aspect of how a process or manufacturing industry conducts its business in the future. Examples of functions that will be impacted include how the companies handle their product development, customer contacts, collaboration with sub-suppliers etc. Many of the expected new digital functions are of course not related to control and operations which is the focus of this paper. In the following sections we will discuss more in detail the current and future implications of the industrial digitalization specifically on control and operations.

4. Current trends

The above introductory sections have already covered some upcoming trends and in this section some of these are further explored. The so called hypes or trends may not all be long-lived but they certainly also affect the expectations of the end users and may indirectly steer the developments of future operations and control. Also, at least for researchers it is always desired to challenge the current state-of-the-art and investigate the true potential of emerging technologies. Below some of the relevant trends are briefly discussed

- Internet of Things: As already discussed above, this is the enabler for cyber-physical systems, which is the core of for instance Industrie 4.0 (Germany) and Smart Manufacturing (US) activities. What it basically means is that any device can be connected to the internet allowing two-way communications across or between plants. This makes new data available also across operations and supports more horizontal applications with decentralized decision making. This fact easily creates unrealistic expectations through the countless opportunities of cross-collaborations between applications. A research question is to identify the main benefits from this collaboration potential. It is important that the engineering and information technology research communities collaborate on these to enable maximum flexibility, as it can result in a paradigm change within the process automation and its functional components.

- Automation Cloud enables software applications to be installed not physically in the plant but anywhere through either intra- or internet connection. This enables the use of much more powerful computing resources (e.g. parallel computing) and easier remote administration. It can also allow purchasing a solution as a service without investing in hardware, thus reducing the investment risk. Technically, even if it is possible to solve larger mathematical problems using the "cloud", still only a few algorithms exist that fully take advantage of this. Definitely, a research challenge is to identify how "unlimited" computing power may affect the life of a normal production facility and to define optimization algorithms that can fully benefit from this and create added value. Methods for systematically evaluating the true optimization potential of a processing plant and the related business models are still missing. Note that a cloud solution can also be hosted locally.
- Big Data technologies aim at analyzing large sets of non-structured data. This can enable new knowledge about the production identifying problems early or creating more accurate data-driven models. For instance, a scheduling function within operations can become more aware and knowledgeable about the underlying and surrounding processes – or the control strategy can be automatically adapted to various situations. It is, nevertheless, most important to have an idea of what one is looking for. The concept of machine learning can be an efficient way to allow analytics to support the optimization by reducing the decision space.
- Smart Grids and Renewable Energy. Smart grids represents in simplified terms the digitalization of the power grid. These energy related topics have increased the importance of reducing the cost or consumption of energy as a target for scheduling and control and opened a bi-directional information flow making it possible to adapt operational decisions to changing energy availability and pricing (industrial demand-side management). Also, new tasks related to energy that have earlier been only considered at control-level may become part of production planning. A challenge is to create efficient demand-side management solutions that explore the opportunities on all levels from process control to short-term planning and to provide the right incentives for companies to adopt these. The last challenge is not trivial due to both fluctuating price developments and political impact.
- Mobility, Unmanned Sites and Remote Operations all contribute to more automated process operations and control. The main idea is to increase the safety of operations, reduce costs and be able to monitor and interact with the process from anywhere at any time. Upcoming standards e.g. 5G with very low latency should enable geographically distributed control solution components. In principle this could be seen as a pure IT-topic. However, not having operators at hand puts more responsibility on the automation and its optimization solutions, which must embed some level of domain competence. This also raises the need to consider a more global perspective possibly leading to very large problem instances. In the long run some of the operator experience will be replaced, which requires fail-safe algorithms also in extreme situations. Furthermore, what kind of remote interaction is needed?
- Service, for instance software-as-a-service (SaaS), provides a large number of opportunities, where basically only the imagination is the limit. Can this be a way to make control and operations solutions more easily deployable or provide a

performance-based solution where the end-customer pays related to the quality improvement of the resulting production or the computational efforts? Will this drive boosting the efficiency of algorithms? A main challenge is related to value creation, i.e. how to measure the offered added value? Another mental hurdle is the trust, as sharing critical information with third-party can be difficult.

In the following sections we will elaborate more on some of these on-going trends and discuss specifically how they concern the control and operations community.

5. Flexibility and agility of industrial production

The term "digitalization" stands for new possibilities provided by the use of more and new types of data, communication infrastructure and computing power. But what drives the industrial user to use these technologies applied to process control and operations? While the high level business objectives in the manufacturing and the processing industries such as productivity, resource efficiency and responsiveness did not change since decades, new market constraints call for a higher degree of flexibility and agility of industrial production. The main reasons for the new market constraints are

- an increasing individualization and fluctuation of end customer demands that propagate through the entire value chain from the customer markets through the manufacturing industry to the processing and primary industry,
- higher volatilities in electricity availability and cost caused by the limited controllability of an increasing amount of renewable energy sources, today mainly wind and solar
- an increasing cost pressure leading to the need to remove buffers and reduce expensive stock of inventories.

Case studies indicate that significant untapped flexibility and agility potential exists both within production facilities and the supply chains (e.g. Hadera et al., 2015; Xu et al., 2012). A broader overview is provided by e.g. Dias and Ierapetritou (2016b) and Stevens and Johnson (2016). To unlock this potential and to use the flexibility in an agile, cost effective and intelligent manner, more automation, automatic control and optimization functionality is required. While in modern plants and factories the degree of automation is already high on device- and unit-level, the networking between units, plants and enterprises is still limited. In order to support more flexibility and agility, the scope for control and operations technologies needs to be increased from devices and units to networks within the enterprises and among enterprises.

Figure 1 illustrates the need for higher flexibility and agility in principle. More flexibility and agility is necessary on all levels of the enterprise operation starting on unit level with faster start-ups and shut-downs, as well as, product and grade changes. Looking at the plant level, the production planning has to be highly responsive and robust at the same time, and it should be integrated with the energy and raw material procurement and the maintenance planning. With the entire enterprise and networks of enterprises in scope, one has to consider that entire value chains will be re-defined and re-allocated between companies more frequently.

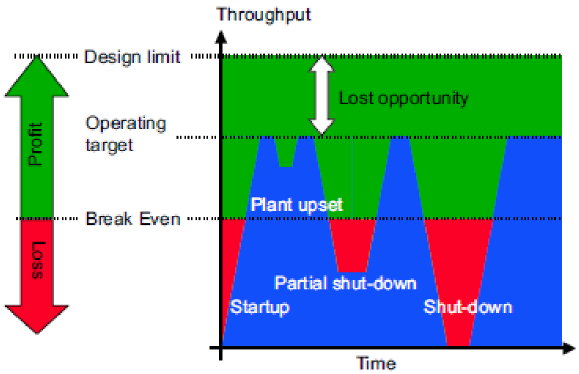

Figure 1. Economic aspects of process flexibility and agility (Sand and Terwiesch, 2013)

From the above it is clear that flexibility and agility of industrial production have an increasing business value which drives the technological development more and more. Combined with the growing amount of available data, better communication infrastructure and more computing power it can be expected that the feasibility limits for control and optimization technologies are pushed further and the operating targets can safely be driven closer to the design limits. Thus, what are the main technological obstacles on the way to more flexibility and agility?

First of all, the increase of the size of the considered systems from individual units to networks of enterprises comes along with an increase of complexity. It is unrealistic to assume, that such a complex system can be controlled and optimized by a "central intelligence". Instead, schemes for distributed control and optimization have to be enhanced such that they fulfill realistic stability, robustness and performance requirements.

Secondly, in face of an increase in the flexibility and agility, new types of dynamics in processes, plants, factories and supply chains have to be considered. The production needs to be kept "under control" on all levels. The impact of fast changes has to be predictable and controllable on all levels including production planning and supply chain operation (Nie et al., 2014). Agility has an impact on the physical wear and lifetime consumption of production facilities. The cost of lifetime consumption needs to be considered and weighted against the benefit of agility. Therefore, production and maintenance planning have to be tightly integrated such that utilization and availability of production assets are considered as two sides of the same coin (Dedopoulos and Shah, 1995; Liu et al., 2014; Biondi et al., 2015; Biondi et al.,2017).

Thirdly, one should not assume that the full information about the system under consideration is automatically available. Data and information about production have a value and are not unconditionally shared between enterprises and sometimes not even between different departments of the same company. Even if business models are in place that monetize and support information sharing, an asymmetry between internal and external information will always remain. Other reasons for incomplete information are insufficient model accuracy, model uncertainties caused by measurement errors, structural discrepancies and limited precision of predictions.

Last but not least, cost-efficient formulation and maintenance of mathematical or formal models as the representation of the physical production and first principles on all levels remains a challenge with increasing importance. Formal models provide usually the basis for the growing number of control and optimization functionalities. Following from the above, paradigms are required that support an easy exchange of models between different owners and the protection of intellectual property at the same time.

6. The future of multivariable control

The multivariable supervisory process control is more and more often done using Model Predictive Control (MPC), see e.g. (García et al., 1999). With its capability to handle constraints and to anticipate future process variables, MPC has become a *de facto* standard for multivariable control in process industry with many different applications (Qin and Badgwell, 2003). Later MPC has been extended to optimally embed more complex logics, e.g. by the capability of switching between various control strategies through the application of binary decision variables. Some of the most prominent approaches are the MLD concept by Bemporad and Morari (1999), multiparametric control by Dua and Pistikopoulos (2000) and mixed-logic dynamic optimization by Oldenburg et al. (2003). Industrial applications of such hybrid MPC solutions are presented already in (Gallestey et al., 2003).

Much academic research around optimization based control has for natural reasons been around how to solve the constrained optimization problem as efficiently as possible. Even though the solver is important, for industrial success of MPC it is much more important to have access to easy to use software tools with a well-defined and efficient engineering workflow for obtaining the model and configuring the controller including finding the appropriate values of the tuning parameters, typically via simulation of the model.

It is also extremely important to include some kind of economic aspects in the optimization. Traditionally this has been handled by solving a steady-state economic optimization formulated as a linear program (LP) giving the setpoints to the MPC. Alternatively it has been suggested to integrate the economic optimization as part of the MPC objective (Zanin et al., 2002; Toumi and Engell, 2004; Rolandi and Romagnoli, 2005; Engell, 2007), leading to what is now commonly referred to as economic model predictive control (eMPC) (Subramanian et al., 2012; Rawlings et al., 2012; Angeli et al., 2012; Amrit et al., 2013). The eMPC concept can also be expanded to cover the nonlinear model predictive control (NMPC) case,. See for example (Lucia et al., 2014) which deals with the robustification of eNMPC.

Perhaps, from an IoT-perspective, even more significant a change has been in moving process control related functions away from the embedded HW controllers to a PC environment. From an industrial perspective the most important issue with MPC is the modeling effort. Today there are MPC installations with hundreds of measured process variables and manipulated variables. However, the increased connectivity and availability of cheap sensors will potentially lead to applications with several thousands of variables. In order to deal with this challenge, new paradigms, for example, combining machine learning and control may become more efficient from a modeling perspective. A deep learning approach has in fact already been applied to data center cooling, see (Evans and Gao, 2016). Similarly there have been attempts to combine deep learning and MPC (Lenz et al., 2014).

7. Increased scope of control and operations

The pressure to connect to and interact with neighboring solutions and systems is increasing (Engell and Harjunkoski, 2012). This makes it for instance very difficult to adapt partly manual and often rule-based decision making to a larger scope due to the complexity of new interlinked (sometimes directly competing) goals and targets, as well as, theoretically unlimited opportunities. To increase the simplicity and define what actually makes sense, what brings additional value and is technically feasible is clearly also an academic challenge.
Through the introduction of the enterprise-wide optimization concept (Grossmann, 2005) enabling the integration of the information and the decision making among various optimization functions that also comprise the supply chain of the company, it is evident that control and e.g. planning and scheduling can and should at least partially be considered jointly. There are several scientific contributions on the topic of integrating scheduling and control and a summary of the research directions is given in, for example Baldea and Harjunkoski (2014) and Dias and Ierapetritou (2016a). The problem gives rise to a mixed integer dynamic optimization (MIDO) problem (Allgor and Barton, 1999), which is non-trivial to solve for larger problem instances. A top-down approach is applied in Chu and You (2012), assuming that the process dynamics are handled as parameters in the scheduling models that can be pre-defined and updated regularly through double feedback loops. Furthermore, scheduling and dynamic optimization have been integrated using state equipment networks in Nie et al. (2012), and by combining enhanced RTN models and a tailored generalized Benders decomposition algorithm, as reported in Nie et al. (2015). The most successful use cases have been applied to continuous processes where the scheduling challenge (number of potential alternatives with respect to sequencing and assignments) is moderate and the main value comes from selecting optimal trajectories for changeovers e.g. in polymer production (Terrazas-Moreno et al., 2007). The theoretical expectations are difficult to prove in practice as this would require quite some operational changes and so far operations and control are still hierarchically separated in most industrial landscapes.

As already pointed out above as well as in Sand and Terwiesch (2013), there is also an increasing integration between the process and power automation. One example of this is the increasing research on industrial demand-side management taking advantage of the fluctuating price information of electricity (Mitra et al., 2014; Hadera et al., 2015; Merkert et al., 2016). Another example is to try to hedge for uncertain power supply while controlling the process. See, for example Besselmann et al. (2016) and Cortinovis et al., (2016), where control of large compressors is designed to ride-through a partial loss of power without tripping the compressor.In a similar fashion, integration to the supply chain level (e.g. Chu et al., 2015; Subramanian et al., 2014; Carlsson et al., 2014) is important for the overall operations in order to receive up-to-date commercial order information, including their priorities. There is also untapped potential integrating the supply chain and energy planning (Waldemarsson et al., 2013). Many of the topics in this section related to sustainability and integration are discussed in the excellent survey by Daoutidis et al. (2016).

To summarize, there are already many research activities aiming to merge earlier separated optimization functions but the main focus is still on modeling. Although the first results are promising often the industrial proof-of-concept is still missing while the methodologies either do not scale-up sufficiently well, or the implementation would require significant efforts and changes in operational culture which might also disturb the running production. A related and relevant question is also the role of the human operator in a scenario of more and more automated production. Whenever the operator is still needed it is very important to consider how the operator interacts with, for example, model-based control and optimization in order not to gradually deteriorate the operators' competence.

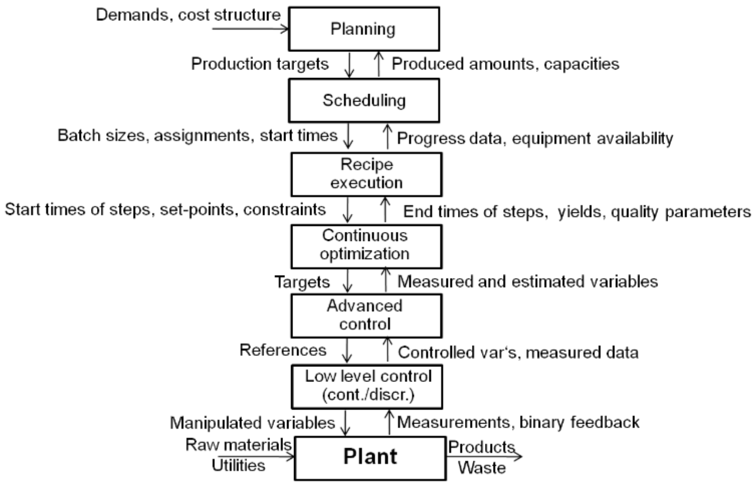

Figure 2. Decision layers in operations – from supply chain to the process (Engell and Harjunkoski, 2012)

8. Future control architecture

All of the above areas of research should ensure, among others, that the provided control and operation is aware of the surrounding environment as well as the underlying process. Figure 2 from Engell and Harjunkoski (2012) illustrates the various dependencies of today's hierarchical decision layers. One can observe that each level typically only communicates with the neighboring ones. Today, however, these functions are in a company often carried out in different departments (sometimes in different locations) using different sets of software tools.

With the recent developments towards internet of things (IoT), we can expect that in the future devices and systems can seamlessly communicate. The most typical IoT-effects are seen in data analytics, where new devices can on-line collect earlier hardly accessible information and feed it into the cloud, where theoretically "unlimited" computing power can be applied for processing the data or optimizing larger-scale problems. Owing to mobility, the results are accessible anywhere and at any time. The impact on process control and other process operations is quite straightforward: They should become more integrated and collaborative and this is supported by the IT-structures. In many industrial visions, the traditional automation pyramid (see Fig. 3), structurally separating process control, scheduling and planning to their own hierarchical levels, has at least partially come to its end.

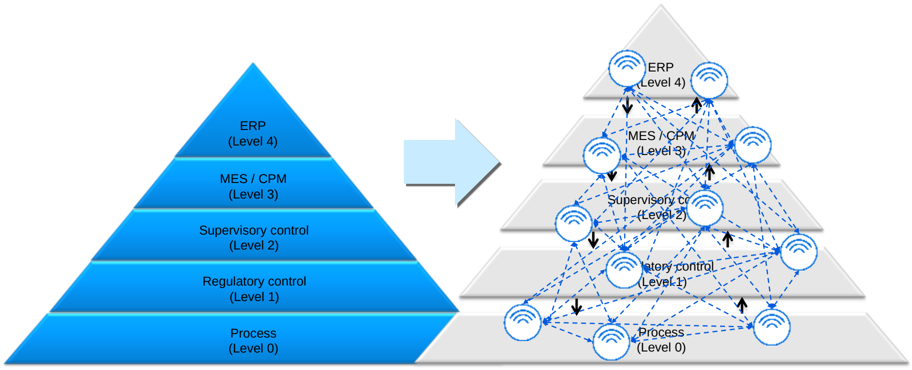

Figure 3. Dissolving the automation pyramid

The hosting levels 2-4 (all functions above regulatory control) may melt together into a single functional software-dominated level, in which all data and information are available to any function in operational planning and execution (see Fig. 3) and tools are offered as “apps” within a common information exchange platform. This calls for more collaborative methodologies and increases the role of software development. In the future, even a PID-controller can simply be an IoT-enabled actuator connected to any PC or even a mobile device.

As seen in Fig. 3, the earlier well-categorized functionalities that logically belonged to one larger solution bundle, such as manufacturing execution system (MES) transforms to a more flexible hierarchy (right side of Fig. 3). The circles represent well-connected functionalities that are in the future only logically mapped to the earlier levels of an automation pyramid based on their function. This directly realizes one of the goals of internet of things: All solutions can directly be connected to the internet/intranet and communicate and exchange data with each other. Thus, instead of having only a handful of connections between the bundled blocks or earlier hierarchical layers, now there are theoretically an unlimited number of communication channels, which opens up a communication challenge, for example in scheduling. Here, in a typical case, order-related information is retrieved from the business systems and the ongoing production is monitored through the control system layer. Nevertheless, the new hierarchy also allows to stay in the established mode and step-wise increase the connectivity when it makes sense. As a consequence, the major functionalities do not disappear despite the fact that the established hierarchical structures are replaced by point-to point communication but this transition also allows that new connections can be easily established between earlier practically isolated systems, for instance by bringing quality, energy, equipment condition, maintenance and operational aspects closer to each other.

In summary, instead of having large monolithic system components, smaller software solutions can contribute, which also makes it easier for “small players”, i.e. companies who only provide a limited or smaller scope of functionalities to enter the market. In the multitude of possible connection points and increasing number of players one key challenge is to create more modular and flexible systems that enable seamless data communication and even can combine earlier separated business models. This ensures that new opportunities can be exploited. ExxonMobil has positioned its visions towards the future control architecture through a set of presentations (Forbes, 2016). Their vision states concretely that a future control system should be built of distributed control nodes

(DCN) that are dedicated single-channel I/O modules with control capability connected to a real-time data service bus. Furthermore, the operations platform should be open and use open-source software. This would enable a much easier revamping of level-1 controllers, which using the current DCS architecture philosophy is in their view both complex and expensive. This means that the entire paradigm of operations and control may change due to a new IT-landscape.

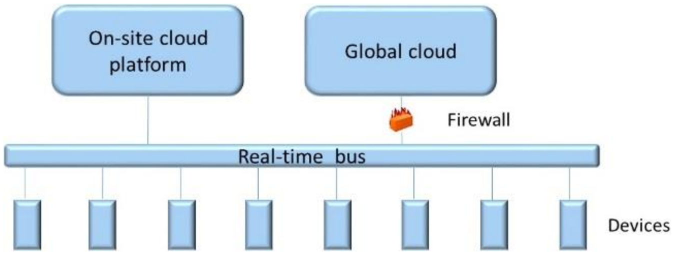

Figure 4. Potential future control architecture

A somewhat simplified picture of the ExxonMobil vision is depicted in Fig. 4. By device is here referred to everything that the control system is connected to, such as measurement devices e.g. sensors and analyzers as well as actuating devices e.g. valves and pumps. At this device level the connection to the common real-time bus could be through a standardized DCN as suggested by ExxonMobil. More futuristic, however, is to assume that all devices have enough intelligence to handle the connectivity and low level control computations themselves, see e.g. (Clark, 2016). An interesting challenge then is where a particular computation should take place. To perform the computing closer to the source is sometimes called edge or fog computing. As pointed out in Ganz et al. (2015), it is already today the case that not all data must be sent to a data historian. For example, when the actuator is a medium-voltage drive that controls the speed, only speed and torque are collected at the control system level, while the current is typically only available inside the drive. Hence we have a trade-off between cloud and edge computing.

In this whole discussion, a natural question is of course which challenges are academic and which ones are topics that should purely be solved by the industrial automation vendors. It seems intuitive that this type of evolution cannot be done without close collaboration and therefore identifying future possibilities and limitations are clearly potential academic questions, whereas the realization of the SW-platforms should be heavily driven by the industry. The most disruptive scenario – utilizing local intelligence without the DCN – clearly will require a considerable standardization effort to harmonize both communication protocols as well as control configurations. For example, notice that there are multiple ways how a PID controller may be parameterized – see e.g. Åström and Hägglund (2006) and Isaksson and Graebe (2002) – which today leads to major proprietary differences how they are implemented. Hence to configure PID loops in a common engineering tool and download for deployment in devices from different vendors will not necessarily be straightforward.

9. Standardized and automatic modeling

One of the major future challenges lies in the modeling effort as well as fidelity of models needed at all levels of automation. Automation suppliers need to continuously cut down the time it takes to produce models for process simulation and optimization solutions as well as tuning of controllers. Very promising results already exist for auto-generation of process models from process topology, see for example (Arroyo et al., 2016) where optical sensors can identify elements and connections from piping and instrumentation diagrams and automatically generate the corresponding model objects for simulation. Whereas this information is mainly qualitative in nature, first steps for also transferring quantitative information to scheduling models can be seen in Harjunkoski and Bauer (2014), where the ISA-95 standard through proper mapping can be used to generate mathematical models including its parameters. Nevertheless, there are still significant amount of open questions regarding modeling efficiency, especially as the model complexity and size are continuously increasing. In factory automation so-called Virtual Commission is already becoming a standard procedure, and this will eventually be the case also for process automation.

In the case where model parameters need to be estimated from real data it has been demonstrated that if enough historic data is available it may not be necessary to actually carry out identification experiments (Bittencourt et. al. 2015). For model based multivariable controllers such as MPC the modeling activity often accounts for 50 percent or more of the total engineering effort in a delivery project. Perhaps there is a potential revival for adaptive control (Chan et. al. 2014). Much engineering effort can also be saved utilizing a modular approach for the configuration of the automation system (Bloch et. al. 2016).

For integration of control and scheduling the main challenge can be identified in the modeling and solution of the resulting multi-level problems. The first question is how to in the first place create a theoretical model of reality and what actually gets lost during this process? Applying e.g. mixed-integer linear programming (MILP) techniques for slower (static) problems limits the models to systems of linear equations. To date non-linear approaches to solve larger-scale MINLP-problems including numerous binary variables have been proven successful only in a few selected examples. Without going into details, other possible techniques to support larger problem instances are timed automata, constraint programming and software agent based methods. Even if there are a number of promising approaches available, a major modeling challenge remains: If we want to optimize the overall operations, how should we model an objective function that captures the various aspects of the problem components? For instance, the most typical scheduling objective of minimizing the make span is not as easily measurable as for instance energy costs, which makes balancing of various objective function components nontrivial. This is partly due to the difficulty of revealing the entire cost structure of companies, which often is a main trade secret. Another major challenge is how to decompose large models without having deep insights into the process or the related value chain.

Following this, a fundamental question in the context of automatic modeling in face of an increasing amount and variety of data is: Under the assumption that all data from the design, the engineering and the past operation of a process is available, what can in principle be modeled automatically and what part of the modeling remains “an art”, i.e. can in principle not be automated? For instance, it is clear that some process dynamics can be identified from historic data, but can operational constraints which are seldom active be identified as well? Are first principles models necessary to optimally control, operate and plan complex processes or can (nearly) optimal controllers, set points and plans be learned from human behavior? Can a theory be developed that – in analogy to controllability and observability of dynamic systems – provides information on the “modelability” of a technical system?

10. Conclusions

In general, the importance of operational and control functions will not diminish. On the contrary, the industrial need for new optimization schemes is growing (Harjunkoski, 2016). New arising communication technologies enables the collection and exchange of information in a much more detailed level creating many opportunities to include and consider a wider scope of aspects related to production. With the ever increasing availability of data and higher level of automation and electrification, e.g. production scheduling and process control cannot anymore be seen as independent solutions.

Instead in the future, control and all levels of operations and operational planning must co-exist in the same environment, supplementing each other without redundancies or competitive functions. The future process control is *synergistic process control*, which benefits from other functions and information across entire process systems – and dilutes the borders between control and operations. This change will require cross-disciplinary collaboration between engineering domains and especially pose many challenges to the process systems engineering community, since despite more intelligent and capable systems, the engineering knowledge is going to play a key role in ensuring efficient, economic and safe process systems also in the future. In particular modeling at all levels will be important. To derive models with the appropriate fidelity at a minimum engineering effort.

Apart from the modeling challenge, one essential question is related to the system architecture of future automation systems. The future automation needs to allow more open interfaces for value-adding components and ideally provide one single data source that is shared among all players. Ensuring that the data exchange is based on established standards is essential in order to support the modularity, flexibility and interexchange-ability of system components. It is likely that distributed control systems (DCS) of today partly lose their roles as coordinating entities and the control and operations functions are partly redefined. Nevertheless, this will be a long process as companies are not willing to change their established and proven systems before there are clear indications of the potential benefits.

Here, academia plays a key role through its capability to invent, verify and refine novel solutions and concepts with long-term strategic goals, partly steered by public funding research agendas, whereas research and development in a typical industry is often bounded by short- or mid-term product development roadmaps and strict profitability requirements, which limits the capability of risk taking. To summarize, the collaboration and inventive contribution from the academia is crucial to tackle the practical challenges faced by the industry – today and tomorrow.

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