Unmanned and Autonomous Systems: Future of Automation in Process and Energy Industries

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Abstract: Process and energy industries have been recognised as adopters of high levels of automation compared to other sectors. Nonetheless, human cognitive input still plays a critical role in the operation of process plants and replication of these cognitive capabilities remains a key challenge for advancing automation levels. In this paper, we provide an analysis of process and energy industries based on a scenario of reduced availability of skilled labour and increased demands for safety, sustainability, and resilience. We consider the different mechanical, sensing, situational awareness, and decision-making tasks involved in the operation of plants and map them to possible realisations of unmanned and autonomous systems. We discuss the implications of current technology capabilities and future technology development perspectives, the factors influencing the complexity of operation in process plants, and the importance of human-machine collaboration. As part of autonomous system capabilities, we consider adaptation as a key capability and we make a connection to adaptation of model-based solutions. We argue that reaching higher and wider levels of autonomy requires a rethink of the design processes for both the physical plants as well as the way automation, control, and safety solutions are conceptualised.

Keywords: Autonomous systems, process automation, process control, machine learning, artificial intelligence, unmanned operation, fault detection, supervisory control, functional safety, human-machine interface, process monitoring, performance optimization

1. INTRODUCTION

The COVID-19 pandemic has highlighted several weaknesses of current industrial production and supply chains (Kamin and Kearns, 2021). Among these weaknesses, strong dependence on human presence in working environments was revealed both by local lockdowns and sicknesses but also because of the limitations of cross-border travel of seasonal workers. The supply chain related problems highlighted the challenges of around-the-clock operation in factories, warehouses, and ports, and additionally strengthened the position of the proponents of more decentralised and localised production and supply chain operations (Sarkis, 2021; Nikolopoulos et al., 2021). A common expectation emerging from these observations is an acceleration in the adoption of automation technologies (Leduc and Zheng, 2020). The observed shortage of workers following the pandemic and the need for continuous operation will motivate building industrial workflows, which can be carried out with minimum dependence on human effort. The decentralised and localised systems mentioned in connection with supply chains, will likely lead to an increased need for skilled labour, unless they are achieved in a more automated way compared to traditional centralised plant operations.

These developments are not exclusively brought by the pandemic. It is highly likely that pre-pandemic investments in automation and digitalisation have already prevented a worse economic outcome from the pandemic. Since several years, automation technologies have been seen as means to bring back manufacturing to high-cost-countries and counter the impact of retiring experienced employees. Some industries, such as offshore oil and gas, have already been looking to automation and remote operations to reduce safety risks but also to handle a shortage of qualified workers and the correspondingly high cost of manned operation (Casey, 2021).

For process and energy industries, we see further pressure for change due to concerns about sustainability and climate change. For instance, the oil and gas industry is looking into carbon capture and hydrogen production to stay relevant in a zero-emissions future (Dawood et al., 2020). Coal fired power plants are likely to be repurposed as energy storage systems, to work with alternative fuels, or to be phased out (Hoffschmidt and Thess, 2018). Chemical process industries are under pressure to reduce their emissions and switch to sustainable feedstocks and energy sources (Schiffer and Manthiram, 2017). Steel production is being re-envisioned to use hydrogen and renewable electricity instead of fossil fuels and alternative fuels are being investigated for the production of cement (Bhaskar et al., 2020; Fennell et al., 2021). New processes and sectors are being developed for chemical recycling, for the processing of novel energy carriers such as hydrogen and ammonia, and for air capture and sequestration of CO_2 (Thiounn and Smith, 2020; Fasihi et al., 2019).

The intersection of the trends of reduced availability of labour, increasing demands for sustainability, and the necessity to combat climate change brings up the possibility of designing a new generation of processes and plants with an embedded

consideration of advanced automation and possibly unmanned operations. Therefore, we believe it is timely to provide an analysis of the current state of automation and operations in the process and energy industries and discuss how higher levels of automation can be achieved and what implications such higher levels of automation will have.

The remainder of this paper is divided into three sections. In Section 2, we first provide an overview of the tasks involved in the operation of process plants and then look at the role human actors and automation currently play for the completion of these tasks and the future possibilities for increasing mechanisation and automation of sensory tasks. In Section 3, we focus on the automation of human cognitive input for unmanned and autonomous operations with considerations of complexity, process modelling, need for adaptation, and the relation of human operators and engineers with autonomous systems in collaborative and complementary settings. We conclude the paper in Section 4 with an outlook based on our observations and provide a discussion for research and development efforts for autonomous systems and advanced automation in the process and energy industries.

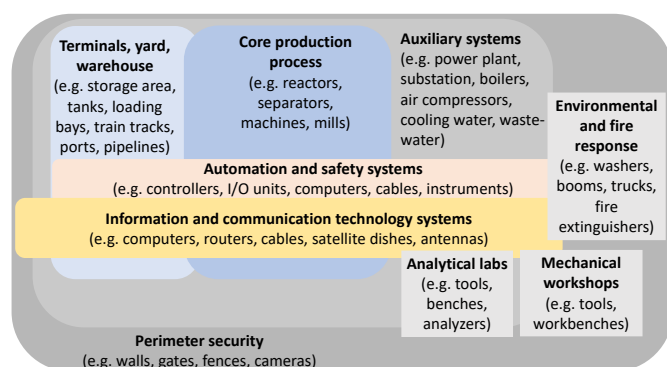## 2. OVERVIEW OF PROCESS PLANT OPERATIONS

Fig. 1. An overview of the constituents of a generic process plant. Overlaps indicate dependencies or connections between the different systems and services.

Process plants have a lifecycle following a sequence of design, engineering, construction, operations, and decommissioning phases. From an automation perspective, all of the tasks over this lifecycle could be considered for automation. In this work, we focus on operations and on the tasks associated with this phase. As capital-intensive investments, process plants are expected to operate for long periods. Further to that, they tend to undergo modifications, expansions, and technology changes during their operational phase. These efforts for continuous improvement and upgrading make up a significant portion of the efforts spent by plant engineers and managers. The changes introduced to the plants combined with the unavoidable loss of performance resulting from operational wear and tear make it challenging to build automation solutions for process plants, because the automation solutions themselves need to be adapted regularly throughout the operational life of process plants. Automation of the tasks during the engineering phase is therefore closely connected the automation of tasks related to the adaptation of the automation system during operation and some of the analysis and discussion in this work can be extended to that phase in the plant lifecycle as well.

2.1 Role of human actors in current process plant operations

Figure 1 shows an overview of the facilities in a typical process plant without the support and service functions for the plant personnel. Functioning of these facilities require efforts in four main *task groups*, namely (i) operations, (ii) maintenance, (iii) continuous improvement, and (iv) emergency response. These effort categories apply to all facilities including the various information and operation technology (IT and OT) elements as well as to the software and algorithms contained within those elements. Considering the work done by the plant personnel, we examine these four categories from the perspective of the role of manual labour, use of human sensory capabilities, and use of human cognitive capabilities.

Role of manual labour:

In a state-of-the-art process plant many operations-related tasks are actuated by the automation and safety systems with some involvement of manual labour, mostly via the operation of machinery such as cranes or forklifts. It is also common for operators to wash and clean equipment or to remove debris and scaling. In tasks related to maintenance and continuous improvement, most work tends to involve human labour. Repair, removal, and replacement of parts or machines are carried out by workers and technicians assisted by necessary tools and machinery. Work in mechanical workshops is mostly manual and laboratories also require manual human interaction. Finally, emergency response for fire can be automated in some plants but, in most cases, human physical intervention is considered as a contingency. Emergency response to leaks and other environmental risks as well as the responses to perimeter security threats generally involve human physical engagement.

Role of human sensory input:

Most sensing needs for the operation of process plants are met by the automation and safety systems and the associated instrumentation. Use of add-on or Internet-of-Things (IoT) sensing solutions as well as increased innate diagnostic capabilities for process machinery have also reduced in-situ monitoring and inspection needs (Ahrend et al., 2019; Sosale and Gebhardt, 2021). Nevertheless, plant operators are often required to tour facilities for observations and for collecting samples and measurements. They are responsible for detecting the abnormalities that can be observed from outside the process vessels. Some operations are carried out in partially or fully exposed settings such as settling pools, conveyor belts, or rotating kilns. Monitoring and inspecting these processes tend to require higher sensory effort from human operators compared to others, which are completely enclosed. In some settings operators observe processes remotely from video feeds. Monitoring and inspection of the hardware components for IT and OT systems as well as the electrical infrastructure is carried out by technicians.

For maintenance related tasks, the characterisation of equipment condition requires a visual inspection in most cases. Performing maintenance actions and their subsequent validation relies on human sensing as well. Detection of fire or environmental emergencies is mostly instrumented but if the

response effort involves human physical engagement, it also implies a coordination via human sensory capabilities. Detection of perimeter security threats is possible via cameras or motion detectors, but situational assessment requires human perception.

Role of human cognitive input:

Even though process plant operations are highly automated for basic control functions, they heavily depend on human cognitive input for sustaining operations (Bauer and Schlake, 2017). Control room operators are responsible for coordinating automatic control functions and monitoring the operation of the plant together with all the auxiliary units. They respond to alarms and alerts, handle disturbances, and ensure that the plant operation is safe and follows the specified operational targets.

Some plants are equipped with advanced process control capabilities, such as model predictive controllers (MPC), which could take part of the cognitive burden from plant operators, but plant operators still monitor and supervise these advanced functions (Qin and Badgwell, 2003). Automation systems of today cannot handle most abnormal events without operator intervention. In such cases operators decide and implement a course of action, usually within a limited time window and with limited situational awareness. In case the operators cannot regain control of the plant, safety systems ensure automatic safe shutdown of the process operation.

Operators, plant engineers, and managers are also required to optimise operational decisions. Some plants employ tools such as real time optimisers (RTO), which could automate the optimisation tasks with the operators and engineers monitoring and supervising the performance of these solutions (Müller et al., 2017). Planning and scheduling of process plant operations are determined by human dispatchers with help of specialised software tools to varying degrees. Other cognitive aspects such as the management of financial operations rely on human cognition. Similarly, the state of the IT systems is monitored especially for cybersecurity threats. Some of these IT security applications could be automated but are supervised by engineers and technicians (Longley, 2019).

For maintenance tasks, engineers and plant managers can be assisted to varying degrees by specialized condition monitoring tools. In some cases, these systems can directly determine maintenance actions and even prescribe changes to operation strategies under human supervision but in most other cases, maintenance decisions are entirely specified by humans. Maintenance, upgrading or reconfiguration of IT and OT software systems are carried out by specialists partially assisted by software solutions except for general software and security updates, which are provided automatically or remotely by corresponding service providers. Similarly, for continuous improvement some plants have access to historical data and analytical tools to calculate various performance indicators, but final interpretations and decisions are carried out by engineers and managers (Qin and Chiang, 2019).

For fire and environmental emergencies, automatic response systems exist but in case the emergency cannot be contained,

human decision making is required. Perimeter security depends entirely on human decision making as well.

2.2 Future of automation for manual labour and human sensory input

The automation of manual work using robotics and robotic teleoperation applications in process and energy industries is an actively developing area (Caiza et al., 2020). These developments for operations such as material handling or process cleaning applications (Giske et al., 2019; Figliolini et al., 2019) can enable removing the dependence on manual labour and eliminate the risk to human life due to work in confined spaces in a process plant. Similar automation developments could reduce the need for manual labour in factory analytical laboratories (Prabhu and Urban, 2017).

In general, mechanisation of regular operations related manual labour is likely to be feasible in most plants due to the repeated and plannable nature of the involved tasks. On the other hand, both operations related troubleshooting such as removal of clogging objects or handling of a jammed machine and the manual labour associated with maintenance tasks pose more serious challenges for direct automation. The troubleshooting work will be difficult to automate due to the high variability of the involved sub-tasks. The maintenance work can involve the replacement of motors, pumps, valves or other similar equipment. The construction of dedicated mechanisation means for these tasks will have very low utilisation rates and the costs are likely to be high due to the involved payloads. In such cases, having either redundant or more durable equipment and a reduced dependence on frequent maintenance would be more attractive than a highly complex mechanical solution, if a reduction of manual labour for these tasks is necessary. Some on-site tasks, such as the work in mechanical workshops, can also be shifted off-site with suitable logistics solutions. Perimeter security can be handled to a large extent via a combination of passive hardening and active robotic means (Huang et al, 2019). Extension of current automation capabilities for firefighting and environmental response could also be feasible in the future (Ausonio et al., 2021; Bogue, 2021). In summary, we see the automation of manual work in process and energy industries to be less constrained by technology capabilities, as compared to the other task categories and to be more of a cost and design challenge.

The automation of monitoring, sensing, and inspection tasks in the process and energy industries has seen a significant increase in technology development over recent years, particularly due to rapid advances in machine learning methods (Salazar et al., 2020; Bae et al, 2018; van Kessel et al., 2018). With a combination of drone-, legged robot-, or rail-based sensing platforms and the adaptation of digital twins, the dependence on routine field inspections by human operators could be significantly reduced or eliminated. On the other hand, similar to the mechanical labour case, the dependence on human perception for activities such as troubleshooting, or maintenance is harder to replace due to the complexity and variety of the involved tasks. For these tasks, remote inspection and observation again via robotic means could be a way to take them off-site. The measures for reducing the dependence on maintenance mentioned above in the

mechanical labour discussion would also eliminate the need to provide on-site human perception for those activities as well.

Similar to the conclusion for mechanical work, the trajectory of current technology developments indicates that in the near future dependence on on-site human perception could be feasible to substitute to a large extent in a cost-effective way, but we do recognise that there are still open problems and challenges for increasing the reliability and wider applicability of the referenced technology developments.

2.3 Future of automation for human cognitive input

Despite the high degree of automation and the extended reach of process control systems in modern plants, human situational awareness and decision-making still play the key role in all task types. The analysis of the future automation potential for these tasks requires the consideration of a number of additional topics such as autonomous systems, the role of complexity, the need for adaptation and a more detailed analysis of the technical challenges involved. These topics will be covered in the remaining sections of this paper.

3. UNMANNED AND AUTONOMOUS OPERATIONS

We focus now on the automation of human cognitive input for process plant operations. We base our analysis of future automation systems on the assumption of a future shortage of qualified personnel. This assumption would cover cases of remote or inaccessible plant sites as well as the case of a future pandemic. A different but equally justified future perspective could prioritise efficiency and maximisation of profit, without necessarily using autonomous systems. These two perspectives are likely to overlap to a certain extent since it is a well-known fact in the industry that most upsets in plant operations are due to human error (Nivolianitou et al., 2006). This is not surprising when the majority of oversight for plant operations are residing with humans, and in most cases operator errors stem from organisational or system design faults. Nonetheless, the computational capabilities, speed of response, and consistency of an algorithmic solution for a particular task are superior to those of a human. Consequently, in the case when an algorithmic solution is available, it can be argued that such solutions will lead to a reduced number of upsets, higher efficiency, and increased profits, which will make them attractive even when a shortage of workers is not a consideration. However, this marginal increase in profit has to be scrutinised against the marginal cost of building the algorithmic solutions, whereas when increased automation is treated as a hard constraint due to a shortage of qualified personnel, it will be scrutinised against the economic feasibility of operating the plant itself. We will use these results to look at complexity as a key dimension to assess algorithmic capabilities and autonomous systems.

3.1 Unmanned operations

Remote operation offers the possibility of taking the cognitive input of human operators off-site from process plants. This possibility can be used to co-locate the workplace with the availability of the workforce, but it can also be used to utilise the workforce to work with multiple sites. The likelihood of the latter arrangement will be reinforced with increasing degree of automation, which already today leaves the operators in a passive supervisory mode for extended periods.

Most process plant operators working on-site are separated in the control room from unit operations, therefore moving them off-site should not create a significantly different working environment. At the same time, in case of upsets operators might need to look for sensory input beyond the available signals in the control system. In addition to the various possible future developments discussed in Section 2.2, additional technologies such as virtual reality headsets with a real-time connection to a camera feed, for example from a drone, can be useful in such a setting for the operators to collect the specific information they need.

The reaction rates of control room operators in process plants are usually not time critical and remote operation will be robust to communication bandwidth problems. However, a disruption in remote communications will leave the plant without any human supervision. Unlike the autonomous system level definitions for vehicles such as cars or aircraft, where the expectation is for a human to take over a task from an autonomous system, this situation would require an autonomous system to take over from a human. Alternatively, an on-site safety solution can be considered to safely shut-down or pause operations in such a situation.

3.2 Autonomous systems

Gamer et al. (2020) provided an in-depth analysis of autonomous systems in the context of industrial plants. They proposed a level-based taxonomy to describe the relative position of human operators and the autonomous system with respect to tasks and responsibilities under varying situations with Level 0 corresponding to no autonomy, and Level 5 to autonomous operation under all circumstances. In this work we will not go into the details of levels of autonomy and focus instead on the aspects of autonomous systems covering the relationship of autonomy and plant complexity, role of plant models, adaptation requirement of autonomous systems, and the interaction of autonomous systems and operators.
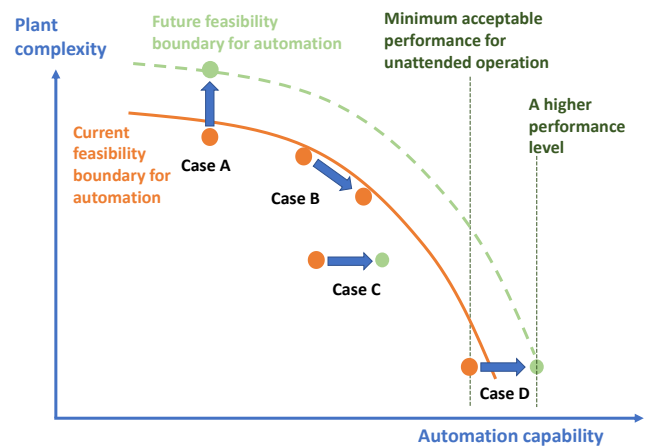

Fig. 2. A conceptual plot showing the relationship between plant complexity and automation capability. The impact of current and future technology limits is illustrated with several example cases.

We define *autonomy* as *the ability of an automation system to complete a task without human intervention*. In the context of this paper, we can use this definition for any complete task happening over a perception-situational awareness-decision making- action chain. This can apply to a feedback control loop in contact with the physical plant or it could apply to an inventory management application making inventory observations in a database and generating orders in another database. Autonomous systems and an overall degree of autonomy can then be assumed to emerge from the aggregation of these autonomous tasks. Some of these tasks might not be possible to carry out autonomously under all circumstances and can require a human to take over, which connects our approach to the taxonomy of the levels of autonomy for autonomous vehicles, but it also allows the coexistence of multiple autonomous entities in a single plant. This approach also allows application of the analysis presented in Section 2 by considering autonomy as the automation of cognitive tasks carried out by human operators, engineers, and technicians.

3.3 Autonomy and complexity

The effort and hence the cost required to build an autonomous solution for a given task scales in proportion to the complexity of that task. This relationship is expected to follow an exponential trend with the cost growing rapidly with increasing task complexity. Therefore, it is essential to understand task complexity when working with autonomous systems. Plants in process and energy industries exhibit varying complexity levels. We divide the main factors increasing complexity into three groups:

(i) *Complexity in plant and process design*. A high number of material recycle streams, a high ratio of recycle flows, a high number of process units the recycle streams span; many connections over a heat integration network; a high number of unit operations sharing the same auxiliary systems such as a steam supply; reduced number and reduced volume of buffer capacities; reduced number of redundant process units; degradation of equipment condition due to design aspects e.g. presence of corrosive substances, dust, coking; and a high ratio of solid or multiphase fluid handling increase complexity.

(ii) *Complexity in plant operation*. A high number of products or product grades; frequent variations in product and product grade changes; and frequent and large variations in plant loads increase complexity.

(iii) *Complexity in plant interfaces*. Uncertain and high variation in feedstock characteristics or quality; and uncertain and high variation in auxiliary sources such as the electrical grid voltage or a heating/cooling utility increase complexity.

The total number of process units and variables will also increase complexity but not as much as the factors from the three groups mentioned above (Wall, 2009). We consider the complexity of the automation system as an independent factor in this analysis and focus on the maximum possible level of automation but the need for a minimum level of automation can also be argued for managing the other complexity factors.

Figure 2 demonstrates the relationship between plant complexity and the aggregate cognitive capability of the automation systems. The vertical lines indicate a performance level. For a given plant, the distance between its level of automation shown as a point in the plot and the performance level at which it operates is the cognitive load carried by the plant operators and engineers. The solid curve and the dashed curve represent the current and possible future technology boundaries, respectively. These boundaries illustrate the relationship between the feasible degree of automation capability and a given level of plant complexity. As an example, a pulp and paper mill will appear as a highly complex plant and will not be possible to automate to a level of unattended operation within current technology boundaries (Case A). Conversely an air separation unit will appear as a less complex plant and could be automated to a level of unattended operation (Case D).

The four cases in Figure 2 show the possible impact of future automation technology. Case B is used to highlight the possibility of achieving a higher degree of automation by reducing the complexity of a plant within a given technology boundary. This could be achieved for example by adding a buffer storage or adding a redundant component. The resulting situation will reduce the cognitive burden on personnel and could be carried out with fewer people. As mentioned at the beginning of Section 3, the cost and benefit analysis for such a change will require the consideration of the circumstances of the plant. Generally, most factors that increase complexity are present in a plant to increase the efficiency and flexibility of the operation and to reduce costs, therefore a reduction in complexity will come with penalties.

Case C is used to highlight that not all plants might adopt a high level of automation and appear at the technology feasibility boundary for their level of complexity. For such cases future technology advances can reduce the cost of adopting automation technologies and can change the economic optimum in favour of a higher degree of automation capability. The corner cases capture high complexity plants (Case A) and plants that are already operating unattended for
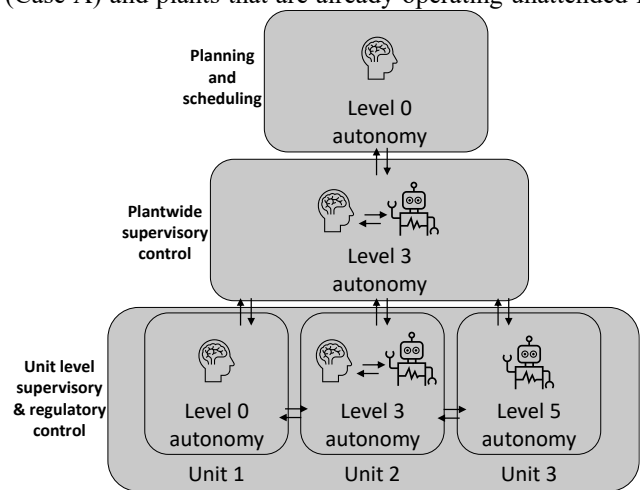
Fig. 3. An example of a plant consisting of three units controlled via a combination of human operators and autonomous agents of varying autonomy levels. The figure illustrates the automation hierarchy and the exchange of information between the different entities.

long periods (Case D). In Case D, technology advances could lead to an increase of the performance of the autonomous system in the form of increased output or fewer number of outages. In Case A, automation technology advances could lead to the realisation of a more complex plant without changing the balance of the cognitive load between humans and autonomous systems.

3.4 Role of plant models for autonomous systems

Use of plant models for process monitoring, control, and optimisation is well established. Automation of many cognitive tasks involving situational awareness and decision making is likely to involve the extension of the capabilities of such models. Therefore, future technology advances will depend on the advances in plant modelling. As mentioned in Section 2, state-of-the art plants today have access to technologies such as digital twins and simulators, which are used to generate insights and assist human personnel with their cognitive tasks. Simulations are being used extensively by autonomous driving technology companies to develop and test autonomous systems (Rong et al., 2020). A challenge for process plants is that their behaviour is not always possible to model accurately especially regarding dynamic responses. This presents a possible obstacle for building autonomous solutions for greenfield plants and could require extensive data collection and testing campaigns as part of the commissioning phase, further increasing costs. As we defined autonomous systems in Section 3.2 to emerge from the aggregation of many autonomous tasks, simulated testing of autonomous solutions for process plants will require a closed-loop integration of these tasks with a plant simulator. However, in case of partial horizontal autonomy, where some unit operations are controlled by an autonomous system and others by human operators, the testing process will require the input of human decisions – which could further complicate testing efforts.

Most critical decision-making tasks carried out by plant operators involve the handling of abnormal operations. Often such decision-making tasks involve discrete actions, such as turning machinery on or off, diverting flows, or activating or deactivating control functions. For handling these problems in an autonomous way, both model-based and model-free decision-making approaches will require a plant model capable of simulating the abnormal operation scenarios of interest. The widely used simulation packages in process and energy industries have currently very limited capabilities for simulating such scenarios and future technology developments should address these shortcomings for reaching higher levels of autonomous operations.

3.5 Autonomy and adaptation

Any industrial process is subject to deterioration and change over its lifetime. The significance of these changes is a factor of complexity as mentioned in Subsection 3.3. Reaching acceptable operating performance without taking into account these changes is difficult. The difficulties arise especially in plants where the changes are significant. This will especially be important for model-based autonomous solutions, where the models need to be updated or adapted to the changes in the plants. The updating of plant models is another cognitive task.

For highly autonomous systems this task could also be made autonomous (Mercangöz et al., 2020). The need for adaptation applies beyond plant models to any operations related task that is handled by autonomous systems, which will require the appropriate characterisation and monitoring of the performance of the different autonomous systems to drive the adaptation processes.

The need for adaptation connects autonomous systems closely with data-driven methods and analysis. Process monitoring and diagnosis solutions are successfully used today in the process and energy industries as a decision-aid tool (Qin, 2012). Automation of the cognitive tasks using such tools will close the loop over operational and possibly also maintenance and continuous improvement related actions. Autonomous systems relying on reinforcement learning for decision-making tasks would also have to utilise process data directly or indirectly (via a process model) to both improve their performance and to adapt to changing conditions. Data-driven solutions such as algorithms for generating forecasts for various external factors, can also be integrated to autonomous solutions and be used to facilitate adaptation processes.

3.6 Autonomous system and human interactions

The purpose of any autonomous system is to fulfil a goal specified by humans. Therefore, regardless of autonomy level any autonomous system has to have a human-machine interface where commands and objectives can be received. In an engineering setting, this interface must be able to return feedback for the commands and objectives to inform the operators about the state of the autonomous system, the feasibility of the commands, and to what extent and at what cost the objectives can be achieved. This information exchange is highly critical for those applications, where a human operator has to take over in case the autonomous system cannot fulfil its function but it is also important in situations, where a fully autonomous system is operating in a collaborative setting along human operators. We illustrate such a situation in Figure 3, which merges the autonomy levels from Gamer et al. (2020) with the automation hierarchy from ANSI-ISA (1995). In this example, the regulatory control for *Unit 3* is under the responsibility of a Level 5 autonomous system, which does not need human supervision for carrying out its function. It has to receive commands and objectives from the plantwide control layer and in turn needs to provide information about its state. This is the first type of information exchange and since the plantwide control layer is autonomous at Level 3 – both a human operator and an autonomous system will be part of it. In addition, the neighbouring units to *Unit 3* are in a possible collaborative setting and *Unit 3* could be envisioned to share information about its state and receive in return information about the state of its neighbours. This is a second type of exchange. Lastly as mentioned before, the plantwide control layer and the unit level control for *Unit 3* are autonomous systems under human supervision and these systems must exchange information with the human operators responsible for the supervision task, which is the third type of information exchange.

The information that can be exchanged with other autonomous or software systems could be designed to maximise system

performance and does not need to be constrained. On the other hand, the information exchange with human operators and supervisors will depend on the context of interaction and for real-time operation needs to be constrained to the capability of the humans for handling this information. These questions involve many other considerations such as human trust in the autonomous system (Shahrdar et al., 2018) and will have to be studied in detail for future automation system designs.

As the number of operators are reduced via the adoption of autonomous systems, fewer operators will be responsible for a larger number of process units. With increasing automation levels the engagement of these fewer human operators with the plants gets reduced. Sometimes referred to as the paradox of automation, this disengagement is thought to decrease the effectiveness of operators especially since they now have to selectively react to only the most critical situations as the automation system handles most other upsets. This could form a boundary beyond which it might not be possible to deploy autonomous systems in an incremental way.

4. SHORT TO MEDIUM TERM OUTLOOK

The analysis provided in this paper indicates that long periods of unattended operation for low-complexity process plants are already technologically possible today. One such plant has been showcased by Shell (Hill, 2020) and several subsea processing plants operate in very much the same way in the North Sea. Reducing plant complexity could make it possible for more plants to reach similar levels of automation, if the economic conditions and the need to reduce the dependence on human labour make it necessary. On the other hand, automating the situational awareness and decision-making tasks carried out by the human personnel is still an open problem. Advanced process control and optimization solutions of today are designed to meet the need of automating plant operation around nominal design conditions. Persistent or abrupt disturbances go beyond the current capabilities of autonomous solutions (Khan et al., 2020) and abnormal operating conditions such as a tripping unit or a strong disturbance such as a temporary power loss, are in most cases handled by the plant operators. For automating these tasks, expert systems with fixed logical structure are too rigid to cover the large variety of possible upsets but a combination of machine learning and symbolic artificial intelligence approaches could be a way to address this challenge. At the same time, training such solutions will require more advanced simulation and computational capabilities. The analysis we provide in this article points to a need of increasing multi-disciplinary work for building autonomous process plants especially between engineering disciplines, computer science, and mathematics. Generally, the process and energy industries can make better use of ongoing technological developments. Conservatism towards advanced automation solutions creates a risk for falling behind in automation capabilities in comparison to discrete manufacturing or logistics applications.

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