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ORIGINAL ARTICLE

Process industries versus discrete processing: how system characteristics affect operator tasks

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Abstract

Despite an increasing level of automation, human operators still play a central role in industrial production. They need to monitor and adjust plant operations, compensate for process deviations, and step in when abnormal situations cannot be handled by the automation but require diagnosis and adaptive intervention. Based on a literature review, the article presents a cross-domain comparison of operator tasks and the associated knowledge and information requirements for process control in the process industries and discrete processing. While the process industries are characterized by a transformation of uniform, shapeless materials in physical or chemical processes, discrete processing is concerned with all subsequent steps in the mass production of consumer goods. It is argued that operator roles in these domains differ considerably. First, we compare technical system characteristics with regard to complex interactions, production processes, materials and products, faults and abnormal situations, and the information available to operators. Second, we describe how these technical system characteristics lay the foundation for similarities and differences in operator roles, focusing on qualification and training, routine task characteristics, dealing with abnormal situations, and the associated challenges for operators. We discuss implications for operator empowerment and operator support by assistance systems.

Keywords Process industries · Discrete processing · Operator tasks · Operator qualification · Process control · Decision making

1 Introduction

Humans are an essential part of industrial production systems. Although most standard situations can be handled by automation, operators need to monitor and adjust the automated system to keep its functioning within specified limits. Moreover, automated systems are not capable of dealing with unanticipated situations. Consider the following two scenarios:

Scenario 1. In a process plant a pump emits an unusual noise, and operators develop and test several hypotheses about the cause. One of them is cavitation, which occurs when the pressure in a medium gets below the medium's vapour pressure threshold while passing through a narrow area. Consequently, gas bubbles are formed and implode against the pump's surface once the narrow area is passed and pressure increases again. To diagnose cavitation, operators must get the pressure above the vapour pressure threshold. However, they can apply at least three strategies, all of which have costs and benefits: (1) increasing pressure by raising the level in a preceding reactor, (2) reducing velocity by slowing down the pump and thereby indirectly increasing pressure, or (3) lowering the medium's vapour pressure threshold by changing the ratio of inflows. When choosing a strategy, several factors must be considered. For instance, strategy 1 only works when the preceding reactor is not too full, strategy 2 means that production is slowed down, and strategy 3 might destroy the product. Therefore, operators need to know about the physical and chemical processes (e.g., mechanisms of cavitation, influence of inflows on product quality), analyze the present situation (e.g., level in

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the reactor, type of product), and balance different trade-offs (e.g., risks for product quality, losses in productivity).

Scenario 2. In a plant that produces and packages yoghurt, paperboard trays filled with yoghurt cups drop off the conveyor belt. The machines are stopped, operators remove the trays, clean up, and restart the machines. After 7 min the fault occurs again. Operators clean and restart the machines, but the fault continues to occur. Nobody knows the cause, and operators simply remove the effect. However, when a particular operator is informed about the problem at shift handover, he replies that he knows the problem, and simply wipes the conveyor belt with a wet sponge. The fault does not re-occur even once during the entire shift. After a systematic analysis, the cause is found to be dust on the conveyor belt that is produced by abrasion of paperboard trays. This dust reduces the friction between the conveyor belt and the paperboard trays. In the conveyor section, the trays are to be rotated by 90° but the reduced friction results in too little rotation (e.g., 85°), and therefore the trays tilt and drop off in the next section. The cause can be fixed by cleaning the conveyor belts from time to time.

Complex industrial systems are notoriously underspecified (Perrow 1984). In Scenario 2, no designer could have anticipated that a sensor for dust on conveyor belts might be needed. However, humans can learn from experience and thus compensate for incomplete knowledge. Moreover, they can adapt to different situations and prioritize different goals according to current demands. When in Scenario 1 a sensitive chemical is produced, operators might opt for a strategy that slows down production but does not interfere with the product. In contrast, when an urgent customer order demands high efficiency, product quality might be weighted less strongly than productivity. Thus, humans compensate for inevitable design shortcomings by learning and acting in flexible, context-dependent ways (Hollnagel 2012).

Based on a literature review, the present article discusses how the requirements for cognitive work that operators are faced with depend on the characteristics of the technical system they work in. The article is concerned with operator jobs embedded in highly automated processes, where their main function is supervisory control (Sheridan 2011): monitoring automated processes and keeping them within certain limits or set points despite disturbances. Jobs range from simple visual tasks (e.g., detecting gummy bears that stick together) to complex mental tasks (e.g., calculating filter cleaning times and adjusting the process accordingly). In contrast, we do not discuss jobs that rely on manual skills, although such jobs certainly exist in the domains we consider.

It is widely recognized that domain characteristics impose specific cognitive demands on operators and thus understanding domain characteristics is an essential prerequisite to understanding operator tasks. For instance, Woods and Hollnagel (1987) present an approach to structuring domain tasks according to the goals to be accomplished, their relations, and the means of accomplishing them. The central unit of analysis is the goal-means relation, or functional interrelation: Goals are achieved by specific processes or functions, while there are many-to-many mappings between the goals and processes: Often, one goal can be achieved by several processes (e.g., a stable temperature can be achieved by regulating mass or using materials with different heat transfer properties) and one process can affect more than one goal (e.g., using different materials will not only affect temperature but also product composition), thus creating side effects. This analysis of goal-means relations is the starting point for characterizing cognitive demands. For instance, if processes have side effects, operators need to be aware of them when selecting the processes for achieving a desired goal.

It has also been discussed how changes in technical systems over time bring about changes in operator tasks and human–machine interaction. The type and degree of automation affect human behaviour and situation awareness (Onnasch et al. 2014), and the changes imposed by automation often transform human practice in unexpected ways and create new tasks or requirements beyond those targeted by the change in function allocation (Dekker and Woods 2002). Changes in the technical system determine what it means to cope with complexity (Hollnagel 2012) or to be in control of a system (Woods and Branlat 2010). For instance, a change from traditional supervisory control to interdependent, multi-layered systems implies that the nature of proactive control is changing: It is no longer sufficient to anticipate how a process parameter is likely to develop but operators must be able to anticipate when the automated controllers will reach the limits of their capacity to adapt the process.

Finally, Human Factors researchers know that a thorough work domain analysis is an essential foundation of interventions to support operators, and analysis methods based on Rasmussen's abstraction hierarchy are available (Naikar et al. 2005). Thus, there is no doubt that system characteristics affect operator tasks and cognitive demands. However, to our knowledge there is no literature that systematically analyzes how differences between two domains' technical systems give rise to differences in tasks and cognitive demands. There is a cross-domain comparison between the jobs of operators in an oil and gas company and nurses in a hospital (Heyer and Grønning 2008). However, these two domains also differ in their purpose (i.e., industrial production system versus healthcare system), and in consequence the comparison stays somewhat abstract. A cross-domain comparison of operator jobs in two production systems has not been published so far. Such a comparison can provide a more fine-grained analysis of job differences between domains and their dependence on characteristics of the respective technical systems. This is important, because a priori it is not clear whether job differences are a necessary consequence of the requirements imposed by the system, have evolved traditionally, or are simply convenient, to name but a few options. For instance, when operators in one domain receive less training than in another, is this because the first domain's technical systems do not pose comparable cognitive challenges, or simply because failure is less costly? In terms of application, understanding the differences in cognitive demands would deepen our understanding of operators' information requirements and thereby help to decide what concepts for operator support from one domain can be transferred to another. Therefore, the article selects two domains, the process industries and discrete processing, and links similarities and differences in their technical systems to similarities and differences in operator jobs.

In the process industries, raw materials are transformed in chemical and physical processes according to formulas and recipes (Dennis and Meredith 2000; Fransoo and Rutten 1994; Moray 2001; Smith 2009; Urbas 2012). There are different branches such as chemicals and petrochemicals, gas processing, power generation, or water and wastewater (Smith 2009), and two basic types of production: continuous and batch (for a comparison see Fransoo and Rutten 1994). One of the main challenges in the process industries is that production is subject to complex interactions between process parameters which are only partly understood (Perrow 1984). The job of operators is to keep the process within specified boundaries, compensate for deviations, and diagnose faults (Kluge 2014; Lau et al. 2012). Their work is a highly proactive and context-dependent activity that can be described as problem solving (Mumaw et al. 2000).

In discrete processing, units of piece goods (e.g., biscuits), fluids and pasty products (e.g., beer and yoghurt), or bulk materials (e.g., rice) are processed and packaged. There are different branches such as food and beverages, pet foods, or toiletries, and two basic types of production: continuous and intermittent (for a comparison see Bleisch et al. 2011). One of the main challenges in discrete processing is that the processing behaviour of products can only be modeled insufficiently. The job of operators is to keep the automated system going and ensure product quality, which encompasses elements of machine operation, process and quality control, and the handling of faults (NOC 2011). Operators' work largely relies on direct observation of the process. In case of faults, they often stop the machines, remove the consequences, and restart the production.

2 Characteristics of the technical systems

Comparing the two domains' technical systems is a prerequisite for understanding operator jobs, because system characteristics create the problem space in which operator interventions represent domain-specific solutions (Lau et al. 2012). Many Human Factors researchers have emphasized that knowing the characteristics of a technical system is essential for understanding its cognitive demands (e.g., Woods and Hollnagel 1987). Still, psychology texts often stay rather vague when it comes to specific system characteristics and their impacts on operators, usually focusing on a small selection of characteristics and analyzing them on a very abstract level. We believe that a deep analysis of the differences between the process industries and discrete processing is essential for understanding differences in operator tasks between these two production systems. Therefore, the first part of the article forms a necessary basis for the second part that deals with operator tasks, strategies, and challenges. In the following sections, we compare the two domains' technical systems with regard to complex interactions, production processes, materials and products, faults and abnormal situations, and the information available to operators. An overview is presented in Table 1.

2.1 System overview

2.1.1 Process industries

Continuous process plants typically are large-scale systems that span many hectares and consist of hundreds of thousands of hardware components (Moray 2001). While each plant is unique, on the level of components plants consist of non-dedicated, general purpose equipment (Dennis and Meredith 2000). Typical components are reactors, pumps, heaters, or agitators, and the final control elements usually are valves (Smith 2009). Plants are causal systems that transform raw materials into products by means of physical and chemical laws (e.g., thermodynamics). Thus, they are constrained by laws of nature, as opposed to intentional systems like universities that are constrained by personal objectives, rules, and practices (Rasmussen et al. 1994). Distributed processes are tightly coupled by continuous streams of mass and energy, which need to be coordinated by plant-wide control strategies. There is plenty of compensation and redundancy between system components, ensuring that the system continues to operate despite component failures (Lau et al. 2012; Mumaw et al. 2000; Urbas 2012). The most important process parameters are temperature, flow, pressure, level, and weight (Smith 2014). Process plants are closed systems in which processes are internally driven by interdependent process parameters. For instance, the liquid outlet temperature of a heat exchanger depends on the steam valve position, steam supply pressure, liquid flow, liquid heat capacity, and many other parameters (Smith 2009). The level of automation is high: During routine operation, most production process run autonomously and the main task of operators is supervisory control (Sheridan 1987, 2011): keeping the process within specified boundaries (see below). However,

Table 1 Comparing the technical systems of the process industries and discrete processing

	Process industries	Discrete processing
System overview		
Scale	Large	Small to medium
Equipment	General purpose equipment	Dedicated machines
Components	Reactors, pumps, heaters, agitators, valves	Forming, filling, cartooning, wrapping, combined
System type	Causal	Causal
Distributed processes	Tightly coupled, need for plant-wide control strategies	Coordinated by the flow of discrete parts, run almost independently
Compensation and redundancy	Plenty	None within a machine, but parallel machines and buffers
Process parameters	Temperature, flow, pressure, level, weight	Force, temperature, time
System	Closed, internally driven	Open, environmental influences
Level of automation	High	Medium to high
Role of safety	High	Negligible
Goals and priorities	Change frequently	Few changes
Complex interactions		
System complexity	High	Low
Source of complexity	Interactions between process parameters, processing steps, common-mode connections	Environmental influences, few connections between process parameters, physical components, and processing operations
Understood by designers	Not fully (process parameters, conditions that make controls non-effective)	Not fully (environmental influences)
Production process		
Typical unit operations	Distillation, crystallization, mechanical separation, chemical reactions	Forming, separating, joining, dispensing, and moving
Type of impact	Indirect (actuators provide necessary conditions)	Direct and indirect
Impact on elements	Similar	Different
Speed of processes	Low	Very high
Time criticality	Not fast but at the right time	Extremely high processing speed
Dynamics	Nonlinear changes, time delays, late feedback	No nonlinear changes, negligible time delays, immediate feedback
Pausing production	Problematic (losses of the whole product)	Possible
Pausing process	Impossible (Eigendynamik)	Possible
Options	Quantitative and qualitative	Quantitative but not qualitative
Materials and products		
Product shape	Undifferentiated mass or fluid	Three-dimensional objects of different materials
Product value	Often high	Low
Diversity of end products	Conti: low, batch: high	High, seasonal variations
Achieving variability	Different recipes, equipment stays the same	Different equipment
Impact of process variations	High, narrow operating ranges	Depends on the product
Variability	Characteristics of raw materials (acidity, viscosity, concentration)	Characteristics of natural materials, perishability
Faults and abnormal situations		
Consequences	Economic and safety-related	Economic
Frequency	Severe accidents are rare, minor disturbances occur daily	Very frequent, depends on the lifetime of machines
Prevention	Safety barriers, layers of protection	Almost none
Typical faults and impacts	Over pressurized reactors and leaks, problems reflected in product parameters, interruptions are rare	Machine stoppages, only affect units of the product
Faulty product	Degrees of deviation from specifications	Geometry, physical damage, contamination
Revising faults	Hardly possible, losses of the entire product	Possible
Fault propagation	Forwards and backwards	Forwards and backwards

Table 1 (continued)

	Process industries	Discrete processing
Perceivability	Not directly perceivable (parameter readings and alarms)	Directly perceivable (open systems)
SOPs	Available only for known faults	Available only for known faults
Information available to operator		
Type of information	Control room: indirect, field: direct	Direct and indirect
Information limits	No sensors, not transferred to control room, not relevant, uncertain validity, noise, presentation in HMI, mismatches between information sources	Encapsulated machines, high speed, some faults do not affect visual product features
HMI	Inconsistent, separate parameters, little information about function	Settings of machines, faults, lack of packaging material

plants still require operator intervention. One reason why appropriate operator involvement is important is safety. Many processes use toxic, explosive, and flammable materials that pose risks for the plant, human health, and the environment. Another reason is that production goals and priorities change frequently, for instance as a function of demand.

2.1.2 Discrete processing

Discrete processing plants are small- to medium-scale systems that use a combination of several machines that work almost independently from each other. For instance, the production of trays with yoghurt cups stacked on a pallet and wrapped in foil requires at least four machines. Dedicated machines perform particular operations, and typical machines are forming machines, filling machines, cartoning machines, wrapping machines, or machines that combine several operations (Mahalik and Nambiar 2010). Plants are causal systems that transform products (e.g., end products from process plants) into discrete units by means of physical laws (e.g., mechanics or thermodynamics). The distributed processes are coordinated by the flow of discrete parts that run almost independently from each other. Therefore, neither control rooms nor plant-wide control strategies are used. There is no redundancy of operations within a single machine, but several machines can work in parallel for crucial production steps. Compensation for machine stoppages is achieved by buffers (Römisch and Weiß 2014). However, redundancy and compensation are used to a lesser degree than in the process industries. The most important process parameters are force, temperature, and time (Bleisch et al. 2011). Plants are open systems and thus environmental influences such as moisture or temperature are an important determinant of processing behaviour. The level of automation is medium to high: 59% of US food manufacturing plants are mostly automated, 35% are somewhat automated, and 6% are sparsely automated (Ilyukhin et al. 2001). In highly automated plants, the process runs autonomously (e.g., machines adjust their processing speed to the amount of incoming material) and operators only have to fix faults and make sure that packaging material is available, while in less automated plants they frequently have to adjust parameters (e.g., machine speed, foil positioning) or perform entire unit operations manually (e.g., putting cookies packed in foil into paperboard boxes). However, due to the complex, variable, and unknown parameters of products and packaging materials, most food plants are run by operator knowledge more than scientific knowledge (Allais et al. 2007a, b). Safety is not a major concern, and changes in production goals and priorities are limited.

2.1.3 Comparing the domains

Plants in the process industries are composed of general purpose equipment, while discrete processing uses complex, specialized machines. Both types of systems are causal transformation systems whose functioning depends on certain process parameters, and both types of processes are highly automated but still require operator involvement. However, only the process industries use large systems with tightly coupled, distributed processes that are coordinated by an integrated process control system. Moreover, in the process industries safety and changing priorities play a larger role. On the other hand, discrete processing is affected by environmental influences more strongly.

2.2 Complex interactions

2.2.1 Process industries

Situations are complex when many variables are strongly interconnected, with these connections being partly intransparent. The system changes dynamically and requires pursuing multiple goals that may be underspecified or in conflict with each other (Dörner 1989; Fischer et al. 2012). Accordingly, process plants are highly complex systems. They are characterized by unplanned or unexpected interactions between process parameters that can be hard to understand. Consider Scenario 1 from the introduction. Increasing the inflow of solvent into a reactor may not only reduce the medium's viscosity but also increase its vapour pressure threshold, thereby leading to cavitation in a pump downstream. This change may also affect other interactions, such as the interplay between pressure and velocity, additionally increasing the risk of cavitation. Interactions also arise between different processing steps within a process. For instance, in batch processes vessel temperature depends on the temperature at the end of a batch, which can lead to unexpected processing behaviours in successive batches (Smith 2014). Unexpected interactions are more likely when the same components are used for different purposes, which is referred to as common-mode connections (Perrow 1984). For instance, sometimes waste heat from one sub-system is used as an input for another to optimize energy recovery and recycling of materials (Smith 2014). Further complexity is added by the plant's dynamic behaviour as discussed in the next section. Due to their complex interactions, process plants are not even fully understood by their designers and engineers, especially with regard to the conditions that make process controls non-effective (Smith 2014).

2.2.2 Discrete processing

Discrete processing plants are less complex than process plants. Despite many variables such as process parameters, physical components, and processing operations, these variables have fewer connections, are connected more linearly, and most interactions are expected and transparent (Perrow 1984). For instance, if yoghurt splashes on the sealing edge of a cup during the filling process, there will be a failure in the sealing process downstream and the seam will leak. The reason is not in the sealing operation but in a previous production step. Although this interaction is unplanned, it is visible and can easily be traced back to a specific source. However, there also are complex interactions in discrete processing which result from environmental influences, especially when working with natural materials. For instance, while an increased moisture enhances the formability of paperboard (Vishtal et al. 2014), it also decreases paperboard strength and thus can lead to fractures. Furthermore, environmental influences interact with varying properties of the products. Although usually the consequences of such interactions can be seen directly when they affect visual product features, they are hard to understand as many environmental influences and product properties are not measured and modelled.

2.2.3 Comparing the domains

Complex interactions are present in both domains. In the process industries, they mainly arise from the nonlinear interplay of process parameters, process-induced couplings between spatially distinct equipment, and unexpected influences between processing steps or runs. In discrete processing, they are due to unknown variations in the products and their interplay with environmental factors. Instead, the influence of process parameters is comparably easy to describe as the systems are linear with no common-mode connections and unintended feedback loops.

2.3 Production process

2.3.1 Process industries

The specific way in which materials are processed is of paramount importance in the process industries (Smith 2009). Processes are composed of unit operations such as distillation, crystallization, mechanical separation, or different chemical reactions (McCabe et al. 1993). The type of impact is indirect: Actuators such as heaters or agitators provide the necessary conditions such as temperature or pressure for the product to change by itself (Mersch et al. 2011; Smith 2014). As products are undifferentiated masses or fluids, process conditions affect all elements in similar ways. For instance, when heating a reactor, the entire chemical in it is affected. The speed of processes is designed to be low, because processes such as energy exchange take time, and many of them are unstable or inefficient under fast conditions (Lau et al. 2012). In fact, most processes are time-critical, but this does not mean "fast" but "at the right time". Time constants, dead times and other process constraints can lead to nonlinear changes in process parameters and time delays between control actions and their effects. For instance, in the petrochemical industry it can take hours or even days for a process to start up (Moray 2001). Therefore, feedback on action consequences often is available only much later. Pausing the production is not an option in most continuous plants as it can lead to losses of the whole product, while in batch plants the consequences tend to be less severe (Smith 2014). Pausing the process usually is impossible as most processes have high degrees of Eigendynamik and continue even in the absence of interventions (Mersch et al. 2011). Thus, in case of faults it is not an option to pause the process and continue later. There are different options for running a process, both quantitatively and qualitatively (Smith 2014): Quantitatively, the operating ranges of process parameters can be manipulated. Qualitatively, operators can use different materials (e.g., cooling with tower water, chilled water, or refrigerated glycol) or different process parameters (e.g., controlling heat transfer via steam flow or temperature).

However, different parameters exhibit different dynamics. For instance, changes of temperature are slower than changes of steam flow. Therefore, variations have different costs and benefits.

2.3.2 Discrete processing

Plants and machines are designed for a specific processing task that proceeds in a stereotypical way. Typical unit operations are forming, separating, joining, dispensing, and moving (Bleisch et al. 2011). The type of impact is both direct and indirect: While some tools such as cutting wires directly transform the product, others such as heaters provide the conditions for change. Different elements are affected in different ways: As the product consists of piece goods, each tool impacts each unit, but the impact is locally limited and the specific location is important. For instance, when heat-sealing tubular bags, only a small area of the bag is heated. Most impacts are of very short duration. For instance, the impact just takes several milliseconds when slicing potatoes or carrots at a cutting speed of more than 4 m s^{-1} (Dowgiallo 2005). The speed of processing is extremely high: For instance, some plants produce 138,000 pieces of confectionery (Majschak 2014) or 600 kg of biscuit per hour (Allais et al. 2007a, b). Most processes are not time-critical as production can be paused and continued in case of faults. Nonlinear changes are untypical and time delays are negligible. For instance, when decreasing feed rate in a bread cutting machine at constant knife speed, the very next slice is thicker already. Although some changes do take time (e.g., increasing the temperature of a sealing jaw), delays are short as only the tools are changed instead of the product itself. Therefore, feedback on action consequences is available immediately. Pausing the production is possible at any time, and in the absence of Eigendynamik this directly translates to pausing the process. There are quantitatively but not qualitatively different options for running a process: While the operating ranges of process parameters can be manipulated, usually there is just one way of achieving a particular effect—or sometimes two, but never many. For instance, to increase the thickness of bread slices, cutting speed can be decreased, and some machines provide the option of increasing the conveying operation.

2.3.3 Comparing the domains

Processes in both domains are composed of different unit operations but there are differences in the way the equipment and process parameters affect the process. In the process industries, the impact of the equipment is indirect, changes take time, and processes cannot simply be paused. In discrete processing, the impact is more direct and fast, and pausing is possible. Moreover, in the process industries there are many different ways of running a process, while in discrete processing a particular effect can usually be achieved in only one specific way.

2.4 Materials and products

2.4.1 Process industries

The product is an undifferentiated mass or fluid that cannot hold its shape without a container (Mersch et al. 2011). While product value can be low in some branches (e.g., wastewater), many products are expensive (e.g., specialty chemicals). Typically, only a few raw materials are turned into a large variety of products via blending and re-splitting operations (Dennis and Meredith 2000; Fransoo and Rutten 1994; Nelson 1983). The diversity of end products differs between continuous and batch processes. In continuous processes, the goal is to produce the same product with the same specifications all the time. In batch processes, highly individual products with different specifications are produced, and variations are achieved via different recipes, while the equipment usually stays the same (Smith 2014). In practice, even for continuous processes it is hard to meet the same product specifications due to complex interactions between process parameters. The impact of process variations on the product is high, and some products have very narrow ranges of suitable operating conditions, for instance requiring temperature control within a range of 0.5 °C (Smith 2014). Another source of variability is the varying characteristics of raw materials such as acidity, viscosity, or concentration of active ingredient. To compensate for this, processing strategies and ingredient proportions need to be adjusted (Fransoo and Rutten 1994).

2.4.2 Discrete processing

Products are three-dimensional objects consisting of different materials. Natural materials or end products of the process industries are processed into separate units. Product value typically is low. The diversity of end products is high. For instance, a dairy company produces about 2,500 end products (Claassen and Van Beek 1993), and most of this diversity can be attributed to different packaging variants. Seasonal variations in the demand for different end products can exist, for instance in the production of chocolate Santa Clauses. Variations between products are achieved by changes in the equipment (Mason et al. 1994) rather than process variations. The impact of process variations depends on the product. For instance, when sealing polymer tubular bags with ultrasound, the sealing time can be varied in a wider range for polypropylene than for polyethylene (Bach et al. 2013). A major source of variability lies in the characteristics of natural materials such as food or paperboard. To compensate, process parameters may need to be adjusted. Perishability can be an issue especially in food processing, so machine stoppages must be fixed quickly.

2.4.3 Comparing the domains

In both domains, the input materials vary in their characteristics, and processes need to be adjusted accordingly. In the process industries, complex interactions make it hard to meet the same product specifications as product quality depends on the way the product is processed, while in discrete processing interventions have less impact on product quality. Moreover, in the process industries some products are expensive and wasting them is not acceptable, while in discrete processing the economic consequences of wastage are smaller.

2.5 Faults and abnormal situations

2.5.1 Process industries

Faults and abnormal situations have economic and safety-related consequences. For instance, in the US they lead to a loss of 10 billion dollars every year (Walker et al. 2011). Some faults are hazardous, but severe accidents are rare due to the plants' inbuilt safety barriers that keep an accident from evolving (Sklet 2006). These "layers of protection" represent an onion-shaped sequence of safeguard operations (CCPS 2017): First, an inherently safer design is used to eliminate events, for instance when using convection cooling to avoid problems associated with the loss of coolant. Second, proactive safeguards such as alarms or pressure relief devices prevent the occurrence of events. Finally, reactive safeguards such as fire protection systems counteract the spread of negative consequences. Thus, the focus on safety is very high in the process industries—if accidents do occur, they typically arise from unforeseen combinations of multiple faults or events that are trivial in isolation (Perrow 1984). In contrast, minor disturbances occur on a day-to-day basis (Embrey 2009), and component failures are always present (Mumaw et al. 2000). Frequent types of faults are overpressurized reactors or leaks (Smith 2014). Problems are mainly reflected in product parameters, while interruptions of the production process are rare. Usually, there is no dichotomy between good and faulty products but different degrees of deviation from the specifications. As process conditions affect all product elements in similar ways, faults can hardly be revised and can lead to losses of the entire product. They can influence different process stages by forwards and backwards propagation. Many faults are not directly perceivable, because the product is contained in vessels and many faults do not change its perceptual characteristics. Instead, information is taken from parameter readings and alarms. For many known faults there are standard operating procedures (SOPs) and even emergency standard operating procedures (ESOPs). However, in case of unknown faults operators often receive insufficient support (Kluge 2014).

2.5.2 Discrete processing

Most faults and abnormal situations only have economic consequences. The frequency of faults depends on the lifetime of machines, being higher in early and late phases (bathtub curve, Klutke et al. 2003). For the early phase an average interval of 4.5 min between consecutive faults has been observed in dairy packaging (Schult et al. 2015). Often the same faults occur again and again. In the intermediate phase fault rates are lower, for instance with an average interval of 748 min in a juice bottling plant (Tsarouhas et al. 2009). Usually, faults result in machine stoppages. Consequences for the product depend on a combination of fault type, product, and equipment. For instance, when chocolate bars were treated with a heat-sealing jaw during a machine stoppage, they need to be scrapped. In contrast, when using a machine with ultrasound sealing, the tools are cold and thus the product is preserved. However, even in the first case faults only affect certain units of the product. Faulty products can be reflected in a wrong geometry, physical damage, or contamination. Faults can propagate forwards and backwards. For instance, when yoghurt splashes on the sealing edge of the cup during the filling process, the seam between the cup and lid film produced in the subsequent sealing process will leak. Preceding production steps are influenced during machine stoppages when the preceding machines are forced to stop. As most processes run in open systems, many faults are directly perceivable. However, some faults such as leaking seams do not change the perceptual characteristics of the product and thus require complex testing. Others can be measured in the plant, such as incorrect filling quantities that are detected by weight measurements. Alarms are available for known faults or causes of machine stoppages, for instance in case of missing packaging material. For many known faults, there are standard operating procedures (SOPs). However, in case of unknown faults operators often receive insufficient support (Schult et al. 2015).

2.5.3 Comparing the domains

Although component failures occur frequently in both domains, their consequences differ. In the process industries, safety systems ensure that the plant keeps functioning, while in discrete processing machine stoppages occur regularly. While in the process industries correct intervention is crucial for reasons of safety, it is considered less important in discrete processing where all that can happen is that production needs to be paused. In the process industries, faults need to be inferred from process parameters and alarms, whereas in discrete processing many faults can be perceived directly.

2.6 Information available to operators

2.6.1 Process industries

Control room operators receive information from indicators and alarms that are presented via the control interface. Additionally, they rely on information from shift handovers, shift logs, checklists, plant documents, and communication with field operators (Mumaw et al. 2000). They mainly use indirect information, because the control room is spatially removed from the process, because processes run in closed vessels and thus measurements are necessary, and because abstract information such as energy transfer rate is not directly perceivable (Lau et al. 2012). There are several limits to the availability, validity, and presentation of information. First, for some information no sensors are available at a reasonable price. They are available for basic measurements such as flows, temperatures, pressure, or levels but not for the exact composition of the product or heat transfer rate (Smith 2009). Such information must be computed or inferred from other measurements. Second, not all measured information is transferred to the control room as such transfer is costly. Third, much of the available information is not relevant, which leads to alarm flooding and nuisance alarms (YA-711 2001): Badly designed alarms do not require operator intervention, and sometimes as much as 50% are not meaningful (Mumaw et al. 2000). Fourth, validity is uncertain as some indicated deviations result from instrumentation failures (Mumaw et al. 2000). Fifth, measurements contain high levels of noise (Hauptmann et al. 2002). Sixth, there are limitations in the way information is presented in human–machine interfaces (HMIs). Usually they have grown over the years, which makes their design inconsistent. Most HMIs provide separate parameter values and low-level information about physics instead of higher-level information about function (Borst et al. 2015; Janzen and Vicente 1998). Finally, there are mismatches between different sources of information such as piping and instrumentation diagrams versus the actual implementation of equipment, which is a potential source of confusion when interacting with field operators. Field operators use sensory information from the plant such as vision, sound, and touch (Kluge et al. 2014). The senses provide qualitatively different information with unquestionable validity that can foster a better understanding of problems (Vicente and Burns 1996). For instance, while in the control room wax-build-up on a valve can only be detected once the valve does not function properly anymore, in the field a gradual build-up can be observed when visually inspecting the valve (Heyer 2009). Therefore, field operators can serve as the control room operator's "eyes and ears" (Skourup and Reigstad 2002), and it is important to combine information from both partners to create shared representations.

2.6.2 Discrete processing

Discrete processing plants usually do not have a control room, and operators working in the plant receive direct and indirect information about technical problems. Direct information is available as most processes run in open systems. When yoghurt drops from the conveyor belt or pralines are squished, problems are directly visible and therefore no complex measurement technology is used. Other problems need to be inferred from indirect information, for mainly three reasons. First, some machines are encapsulated for hygienic and operator safety reasons. Second, due to their high operation speeds many processes make it impossible to visually inspect individual product items. Third, some faults do not affect visual product features, such as leaks in yoghurt cups caused by the splashing of yoghurt during the filling process. Accordingly, some problems can be detected only in random quality checks. Further indirect information is available from human–machine interfaces (HMIs) such as machine control panels, video monitors, or gauges. HMIs provide information about the settings of machines and problems such as the lack of packaging material. Moreover, signal pillars comparable to traffic lights with red, yellow and green lights signal machine stoppages or missing packaging material by flashing red lights combined with an acoustic signal. Alarms inform operators about technical faults, while alarms for deviations in process parameters are rare.

2.6.3 Comparing the domains

In the process industries, processes cannot be seen directly and therefore lots of measurement technology is installed, which provides indirect information to control room operators. There are huge amounts of data, but its interpretation underlies several limitations of availability and validity. Some sensory information can be provided by field operators. In contrast, in discrete processing operators use direct sensory and indirect information, but all information is restricted to a specific processing area. Consequently, while operators in the process industries are confronted with problems of information overload, in discrete processing they face the complementary challenge of not receiving enough information.

3 Operator tasks, strategies, and challenges

As a consequence of different characteristics of the technical systems in the two domains, operators perform different tasks and are faced with different challenges. The present section describes the contents of operator training, routine tasks, dealing with faults and abnormal situations, and the associated challenges. An overview is presented in Table 2. While the Human Factors literature provides a large knowledge base on operator tasks and cognitive requirements in the process industries, literature is sparse for discrete processing. Consequently, the scientific basis for a systematic review is limited. Instead, much of our information is based on informal observations in a number of companies and discussions with domain experts. As this information is not sufficiently objective, we pursue the following strategy: Based on the literature review of the process industries, we set up the discrete processing parts as a tentative comparison informed by the facts from the technical section. This description is somewhat speculative and should serve to stimulate future research.

3.1 Operator qualification and training

3.1.1 Process industries

Operators receive comparably high levels of education before entering their job. In Germany they typically have finished secondary school and then undergone a 3-year vocational training as chemical technicians or related professions. In this competency-based training (Embrey 2009), they learn about basic principles in the classroom and acquire most operational and procedural skills while working in a company, alternating in cycles of 2 weeks. Sometimes, parts of the training take place in training simulators which are replications of control rooms and allow for experience-based learning (Urbas 1999). Standard training is suitable to prepare trainees for routine operation but does not teach some of the more complex skills as crucial components are lacking (Embrey 2009; Kluge et al. 2014): Trainees tend to receive inadequate preparation for dealing with process disturbances and are not prepared sufficiently for crew coordination. Most skills are acquired on the job as they demand extensive experience (Smith 2014). The following types of knowledge are acquired through practical experience (Yin and Laberge 2010): First, operators learn the skills, routines, and SOPs of a company. Second, they develop generalizable knowledge about situations that have a similar deep structure. Third, they gain abstract system knowledge, for instance about the relations between physical components or process parameters. Usually, control room operators have gained much of their understanding from working directly in the plant as field operators (Yin and Laberge 2010), and field operators estimate that it takes 1 year to understand specific areas of a plant, and 5 years to understand the whole plant (Heyer 2009). The conditions for knowledge acquisition are favourable as operators typically have permanent jobs.

3.1.2 Discrete processing

Operators typically have low levels of education, although operator qualification differs between countries (Mason et al. 1994). For many tasks, no specific qualification is required and no dedicated job training is provided. Especially for quality control tasks, migrant or seasonal workers are hired who only receive a brief introduction to the machines and tasks (e.g., how to detect and pick out pralines that do not conform to standards, how to stop machines, how to refill packaging material). On the other hand, there are more demanding jobs such as the supervision of complex machines that require adaptations according to current process requirements. Such tasks are often performed by workers with permanent jobs. Many operators only supervise a single production step or machine. Accordingly, they gain experience in a specific task but cannot develop an understanding of the overall process. Most skills are acquired on the job, and process control heavily relies on operator experience (Allais et al. 2007b). The following types of knowledge are acquired through practical experience: First, operators learn the skills, routines, and SOPs of a company. Perceptual expertise is developed in the evaluation of sensory product properties, and procedural expertise is needed for machine adjustments. Second, experience in handling faults and process deviations is developed as the same faults re-occur frequently.

3.1.3 Integration

While operators in the processing industries receive extensive training before entering their job, in discrete processing they do not. In both domains, on-the-job training is crucial, but different competencies are acquired: While in the process industries operators can develop an understanding of the process, in discrete processing they mainly develop procedural and perceptual skills in a specific task. Why can discrete processing afford to employ operators with such low qualification? Certainly, the reason is not that operator qualification is inconsequential as it leads to reduced productivity and increased wastage in this domain (Mason et al. 1994). However, it does not make production impossible altogether. First, discrete processing does not use tightly coupled, distributed processes that need to be coordinated. Accordingly, plants can be operated even without an overall picture of the system. Second, there are less complex interactions between process parameters, and operator actions have limited impacts on product quality. Thus, processes can be run even when not understanding the interplay of process parameters. Third, different production contexts and changing priorities play a smaller role, which makes adaptive operator action and strategy selection less crucial. Fourth, the process affects only some elements of the product at a

Table 2 Comparing operator tasks, roles, and challenges between the process industries and discrete processing

	Process industries	Discrete processing
Operator qualification and training		
Level of education	High (vocational training)	Low (no dedicated job training)
Training contents	Competency-based training of basic principles and routine operation (classroom, plant, simulators)	Brief introduction to the machines and tasks (more for supervision of complex machines)
On-the-job training	Important	Often the only source of training
Knowledge acquired on the job	Skills, routines, SOPs, generalizable knowledge about situations, abstract system knowledge	Skills, routines, and SOPs (often single production step or machine), perceptual and procedural expertise, experience in fault handling
Conditions for learning	Good (permanent jobs)	Poor (few permanent jobs, many migrant or seasonal workers)
Routine task characteristics		
Content	Adaptation to minimize or eliminate unwanted variability	Keeping production going, meeting specifications, quality control, dealing with faults
Specificity of interventions	Continuous and quantitative, few SOPs for adjustments, required values depend on context	Qualitative, few instrumental measurements
Human-automation task sharing	Supervisory control (operators monitor and compensate)	Operators provide the preconditions
Frequency of interventions	Low	High
Repetitiveness	Medium to high	High
Types of control	Production control, compensatory control, corrective control	Production control, compensatory control, corrective control
Monitoring	Very active, 3 components (familiarizing, top-down sampling, information processing), strategies for manipulating and organizing information	Passive, driven by disturbances, vigilance and scanning, no need for mental models, perceiving effects of process in products, reacting to alarms
Time perspective of control	Proactive (anticipation and planning)	Mainly reactive (stopping machines, cleaning up)
Degrees of freedom	Many	Few
Responsibility	High	Low
Dealing with abnormal situations		
Detecting	Easy due to alarms, difficulties in identifying affected components due to alarm flooding and data overload	Easy (usually few sensors but salient symptoms)
Diagnosing	Difficult (common-mode failures and overlapping faults), problems in hypothesis generation	Difficult (due to many influences, fault propagation, and low qualification)
Dealing with faults	Relying on knowledge, maintaining concurrent representations, modes of processing, nonlinear reasoning, balancing control needs	Compensatory control (stopping, cleaning up, re-starting), often just removing symptoms, procedural knowledge gained from experience
Challenges for operators		
Understanding the process	Essential	Often inadequate
Scale	Many components and parameters, incomplete knowledge, information overload and noise (requires prioritizing, selecting, integrating)	Specific process segment, little information (no overload and integration, limited basis for understanding)
Complex interactions	Considering mutual influences, forming appropriate situation models (hampered by Eigendynamik, delayed feedback, nonlinear changes, and variability of processes)	No complex system dynamics but limited understanding of interconnections between machines, product properties, and environment (hampered by simplicity of HMIs)
Goal state	Underspecified, requires goal setting and dynamic prioritization	Fully specified, clear hierarchy of constraint
Time pressure	Usually not important	High

time, and most processes can be paused. Therefore, in case of negative impacts of operator actions, only parts of the product are wasted, the consequences can be removed, and the process can continue normally. Finally, products are cheap and safety is not a major issue, so the costs and risks of inappropriate operator actions are lower. These differences between the domains lead to different requirements for operators to adapt their actions to the current situation, and different risks associated with such adaptations. In short, the process industries cannot do without flexible adaptation by operators, and thus it is mandatory to equip operators with the system knowledge and understanding that allows them to perform adaptations appropriately. Conversely, in discrete processing inappropriate adaptations are less costly and thus adaptation is neither encouraged nor supported by training.

3.2 Routine task characteristics

3.2.1 Process industries

Routine tasks are mainly concerned with an adaptation to the current production context in order to minimize or eliminate unwanted variability. The specific control actions are continuous and quantitative. For instance, operators do not merely open a valve but adjust its opening to the current process state, often by using feedback such as flow and pressure changes (Smith 2014). SOPs for such adjustments are rare, because the required values depend on the production context and thus cannot be specified exactly in advance. Variations in raw materials may require different parameter settings, different ingredient proportions, or even additional materials (Fransoo and Rutten 1994). Task-sharing between human and automation implies that the automation does the basic work and operators compensate for the things it cannot do. Thus, operator tasks are concerned with supervisory control (Sheridan 2011). In continuous processes, the frequency of operator interventions is low. On average, they perform 5–6 actions per hour, and each of them takes about 1–4 min (Johannsen 1993). In batch processes, more operator involvement is required. Repetitiveness of tasks is medium to high: While the general process is repetitive, many specific operator actions are not as they require adaptation to the current process state. Operators perform different types of control (Lau et al. 2012). First, production control is concerned with changing and optimizing the system state by controlling the material and energy flows. Second, upon detecting a deviation, compensatory control is required: stabilizing the process even when the source of the problem is unknown. Third, corrective control sets in after having identified the problem. Only the first type concerns routine situations, while the latter two are relevant for dealing with abnormal situations as discussed in the next section.

As a precondition for process control, operators need to monitor the system (for a detailed characterization of monitoring activities see Mumaw et al. 2000). However, in contrast to some other domains, monitoring is not a matter of vigilance (Moray and Haudegond 1998): Operators do not wait for the occurrence of deviations. Instead, monitoring is a cognitively demanding activity of problem solving (Mumaw et al. 2000): Operators engage in an active search, integration, and construction of information. This entails three components (Lau et al. 2012): First, operators need to familiarize themselves with the current production context, because the same information can mean different things in different contexts. For instance, while an alarm may indicate a critical condition during standard operation, it may be completely normal during maintenance (Vicente et al. 2004). Second, operators engage in active, top-down sampling of information, because the abundance of available parameters makes it impossible to attend to all of them (Mumaw et al. 2000). Information selection therefore depends on mental models of the process. While novice operators tend to browse process displays in order not to miss anything, expert operators are much more focused in switching between a small set of displays (Heyer 2009). Third, operators engage in thorough information processing to make valid judgments. This is necessary due to complex process dynamics, but also because the meaning of alarms depends on the current production context. Accordingly, operators cannot simply check whether parameters fall within specified ranges but need to perform complex cognitive operations to detect problems (Moray and Haudegond 1998). To facilitate monitoring, operators use different strategies for actively manipulating and organizing the available information (Heyer 2009; Mumaw et al. 2000; Vicente et al. 2004), for instance by configuring alarms, adapting information display in the HMI, or off-loading cognitive demands to the environment by using external cues such as sticky notes.

Operator performance critically relies on proactive control (Roth and Woods 1988; Yin et al. 2008): controlling the process in ways that prevent deviations in the first place. For instance, at shift handovers operators often write down the values of process parameters that may cause problems, so that they can monitor them extra closely (Mumaw et al. 2000). However, to make proactive control possible, not only monitoring but also anticipation and planning are needed. For instance, operators do not have to wait for an alarm to indicate that a filter is clogged but can estimate the remaining time until cleaning is due via the differential pressure before and after the filter. Operators have many degrees of freedom in strategy selection, but this also means high responsibility. As the product is a uniform mass and all elements are affected in similar ways, operator interventions have strong impacts and often cannot be revised.

3.2.2 Discrete processing

Operators work directly in the plant where they are responsible for a specific process section. An operator can be assigned to a segment of a conveyor belt, a single machine, a group of two or more machines, but not the entire plant. The work of operators aims at keeping the production going while achieving and maintaining detailed product specifications despite variations in products and environmental conditions (Mason et al. 1994). Operators provide the preconditions for the automated process to run, check the products, and make corrective adjustments to the machines (NOC 2011). An important task in discrete processing is quality control. To this end, operators perform a few instrumental measurements (e.g., weighting product samples) but mainly rely on sensory information such as sight, smell, and touch (Allais et al. 2007a). For instance, in biscuit manufacturing five product quality criteria are assessed: development, crumb aeration, shape irregularity, colour of sugaring, and colour of sole (Edoura-Gaena et al. 2006). Even in highly automated plants operator interventions are frequent (Mason et al. 1994). For instance, during product quality control it can be necessary to pick out a suboptimal item every few seconds, and the rectification of faults can be necessary as often as every 4.5 min (Schult et al. 2015). Due to the frequency and similarity of faults, dealing with them can be considered a routine task, and most tasks are highly repetitive. Just like in the process industries, the types of control can be distinguished into production control, compensatory control, and corrective control (Lau et al. 2012). The goal of production control is to maintain the product as regular as possible by making adaptations to the machines (Mason et al. 1994). Such adaptations are either made by setting process parameters (e.g., adjusting conveyor belt speed) or mechanically changing the machines (e.g., decreasing the height of a downholder). Operators' main responsibility is compensatory control, which is discussed in the next section.

Monitoring is rather passive and driven by disturbances in a bottom-up manner. It can be a matter of vigilance, for instance when operators observe a stream of cookies for 8 h a shift to pick out broken ones. Such tasks are a matter of visual scanning and do not presuppose mental models: A broken cookie is a broken cookie, regardless of the current specifications. Monitoring is accomplished by perceiving the effects of process parameters rather than the parameters themselves, which facilitates the detection of problems compared to situations where they must be inferred from indirect information such as sensor data. Similarly, as alarms always indicate problems that need to be fixed, thorough information processing and judgment are of minor importance. Performance relies on reactive control: In case of deviations, operators need to react quickly and appropriately, for instance by stopping the machines or removing suboptimal product items. Proactive control is necessary in some workplaces (e.g., operation of complex machines) but is much less common than in the process industries, presumably due to low operator qualification. Operators have few degrees of freedom in strategy selection. Unsuccessful actions can easily be revised: As the product is a set of individual units, operator actions only affect parts of it, which can be removed (Fransoo and Rutten 1994).

3.2.3 Integration

In the process industries, routine operation is concerned with the minimization of unwanted variability, and operators must take the current production context into account for the appropriate selection among strategies with different costs and benefits. In discrete processing, routine operation intends to keep the process going and remove disturbances. Interventions are more frequent and repetitive, and often there is a specific correct way of acting. A possible explanation for this difference is that process plants are safety–critical systems, and thus in their design most problems have been analyzed, eliminated, or compensated for. Accordingly, few operator interventions are needed and if they are, they fulfil a function that cannot be handled well by automation: flexible adaptation to changing constraints. In contrast, the design of discrete processing plants is less focused on risk analysis and elimination, so many unknown factors have unintended effects and need to be fixed repeatedly. Another difference is that monitoring requires an active sampling and processing of information in the process industries, while it is more passive and based on simple scanning in discrete processing. This is possible because faults locally affect sensory product characteristics, while in the process industries they are observable only in the patterns emerging from several process parameters that need to be sampled and integrated. A third difference is that control is highly proactive in the process industries but more reactive in discrete processing. Reactive control would be insufficient in the process industries because many negative consequences cannot be revised, and due to time delays reactions would often be too late. Instead, discrete processing is fast, provides immediate feedback, and action consequences are visible. These characteristics also make online quality control possible in discrete processing. As the product consists of individual parts with only some being affected by faults, quality control allows for them to be removed without changing or pausing the process.

3.3 Dealing with abnormal situations

3.3.1 Process industries

At times, operators are confronted with non-routine situations that occur infrequently and require them to engage in reasoning and problem solving, for instance in case of unknown faults. The handling of faults involves several component activities: Operators need to detect that something is wrong, diagnose the cause, and implement control actions to compensate for the fault or remove it (Lau et al. 2012; Patrick et al. 2006). Detecting a fault usually is easy as deviations in process parameters are indicated by alarms. Consequently, operators report that for fault detection they rely on the alarm system instead of continuously checking the process parameters (Vicente et al. 2001). Difficulties arise in the identification of the affected component, because the high number of alarms and abundance of data in typical HMIs make it hard to select and integrate relevant information (Borst et al. 2015). Diagnosing faults is difficult, especially for common-mode failures (Perrow 1984) and multiple overlapping faults (Patrick et al. 1999). Problems occur most often in the hypothesis generation phase because operators generate hypotheses too quickly and focus on a single one instead of generating multiple alternatives (Patrick et al. 1999). The cognitive activities during diagnosis are concerned with a creative application of system knowledge. This entails five components (Lau et al. 2012). First, operators extensively rely on domain and system knowledge. Consider Scenario 1 from the introduction, where selecting an appropriate strategy is only possible when knowing the underlying physical mechanisms and thus being able to estimate how different interventions will affect the process. Second, operators maintain several concurrent representations of the plant, and flexibly switch between them depending on the current diagnosis task. For instance, they may see a pump either as a technical device with properties X and Y or as part of a functional unit for exchanging fluids. Third, they use different modes of information processing in terms of the skills, rules, knowledge framework (Rasmussen 1983). For instance, they can recognize when no suitable experiences or SOPs are available, and instead engage in exploratory behaviour. Fourth, they engage in nonlinear reasoning, which means that they incrementally revise and refine hypotheses. Fifth, they balance competing control needs, and quickly change from planful action to immediate reaction.

3.3.2 Discrete processing

In discrete processing, faults and machine stoppages can hardly be called abnormal situations as they occur so frequently. Typically, faults are small and relatively easy to handle—the problem is their frequency. Detecting a fault usually is easy, although no sensors are available for many relevant parameters and alarms only indicate known faults. However, faults often cause salient symptoms. For instance, when the product drops off the conveyor belt or is physically destroyed, this is sure to be noticed. Diagnosing faults is difficult due to the variety of influences of material properties and environmental factors. Moreover, diagnosis can be complicated by fault propagation: Often a symptom shows up only one or several machines after the machine that has actually caused the problem. Due to their low qualification, operators rarely have the capacity to diagnose faults by themselves but usually call maintenance technicians. Instead, they mainly perform compensatory control: stopping the machines, cleaning up, and re-starting the process. For most faults, reification takes less than 2 min (Schult et al. 2015). However, often operators merely remove the symptoms instead of permanently solving the problem. If faults cannot be handled by operators, technicians fix the problem. When operators handle faults by themselves, their actions usually are informed by procedural knowledge gained from experience rather than domain and system knowledge: As the same faults re-occur, operators develop strategies of handling them. For instance, the operator in Scenario 2 in the introduction had learned how to prevent the dropping of yoghurt trays by cleaning the conveyor belt from time to time.

3.3.3 Integration

Faults can be considered an abnormal situation in the process industries but occur on a regular basis in discrete processing. Detecting a deviation is easy in both domains, via alarms in the process industries and by direct perception in discrete processing. Fault diagnosis calls for the creative application of system knowledge in the process industries, while discrete processing operators are less concerned with diagnosis. Compensatory and corrective control is performed in both domains. However, in discrete processing these actions tend to be more immediate and aimed at fixing the symptoms. Correction relies on system knowledge in the process industries, and procedural knowledge gained from experience in discrete processing. These differences presumably are a consequence of different operator qualifications: Only when having sufficient system knowledge there is something to apply in creative and context-dependent ways. Conversely, this lack of knowledge might also contribute to discrete processing operators' frequent use of quick fixes. At the same time, the high rates and repetitive nature of faults foster such strategies, while in the process industries faults are highly individual and cannot be handled by stereotypic actions.

3.4 Challenges for operators

3.4.1 Process industries

Process plants cannot be operated by relying on procedures alone—it is essential to understand the process (Yin and

Laberge 2010). However, this is challenging due to the plants' large scale, the processes' complex interactions, and the high level of automation (Lau et al. 2012). As a result of the large scale, there is an abundance of components and parameters to be considered, and thus operators have incomplete knowledge. Their domain knowledge is not high-level chemical engineering theory but based on the way their specific plant works (Embrey 2009), they can describe the connections between various components, and explain their effects on the production process (Yin and Laberge 2010). However, they often do not know how different variants of equipment change the interaction of process parameters, or when automatic control becomes non-effective (Smith 2014). Another challenge associated with the large scale is information overload and noise (Mumaw et al. 2000). Operators need to prioritize, select, and integrate information that is distributed across the technical system and control interface. They often monitor 3–4 screens, and thus attention management is crucial. This is hampered by the poor quality of HMIs which forces operators to perform mental transformation (e.g., when the level of different reactors is provided in different units such as meters, volume, and percent) and integration (e.g., combining different inflows to infer mass balance). Similarly, noise makes it necessary for operators to decide which fluctuations are relevant, and at times all they can do is base their actions on assumptions. Operators need to take complex interactions into account—just focusing on a particular component or parameter does not work due to their mutual influences (Lau et al. 2012). For instance, the required waiting time for changing pressure rates depends on vessel size, product type, and temperature (Smith 2014). Therefore, operators need to form appropriate situation models that include plant physics and function. They enable operators to represent cause-effect relations and explain events, understand and integrate data, fill in for non-monitored parameters, conceive of the plant state at higher levels of abstraction (i.e., system performance, goal achievement), and run mental simulations to anticipate outcomes (Vicente et al. 2004). The formation of such models is complicated by the system's Eigendynamik, delayed feedback, and nonlinear changes. Moreover, the variability of processes makes exact predictions of events and their time courses impossible even for expert operators (Cara and Lagrange 1999). Dealing with complexity is complicated by the fact that the goal state is underspecified. General goals set by the management typically are insufficient as guidelines for control decisions (Bainbridge 1981), the target changes dynamically as a function of demand, and optimal parameter values differ between situations. Accordingly, operators need to engage in goal setting and dynamic prioritization. For instance, as a safety-relevant alarm comes in, they need to set other tasks aside and fully focus their attention on the current problem (Vicente et al. 2004). However, despite in some abnormal situations, time pressure is not a central issue.

3.4.2 Discrete processing

Operators often do not have a thorough understanding of the process. They are responsible only for a specific process segment and thus only receive small amounts of information. On the one hand, this means that dealing with information overload and noise is not a significant problem, and it is not necessary to integrate different information sources. On the other hand, it hardly gives operators a chance to understand how different parts of the process play together. The understanding of individual machines is limited, too. Typically, operators know their machine's basic functions and how to deal with frequent faults. However, it is a challenge even for expert operators to understand why the machine is acting the way it does, due to the complexity of machines, the influence of environmental conditions, and the varying properties of natural goods. This is exacerbated by the simplicity of HMIs that provide a few basic alarms and mainly tell operators what to do, instead of providing in-depth information about the process. Regarding the plant's processing behaviour, several challenges are absent in discrete processing: There is no need to deal with Eigendynamik, changes and cause-effect relations are mostly linear, and feedback is immediate. Highly stereotypical processes make exact predictions of events and their time courses quite feasible. A consequence is that operators can run the machines even without adequate mental models. The goal state is fully specified. Exact product specifications are available and targets usually do not change as a function of demand. Demand can determine the type and quantity of the product to be produced but does not affect the required specifications within product types. The constraints to be met have a clear hierarchy. For instance, operators in biscuit production need to make sure to (1) maintain a continuous line flow, (2) meet the specifications for moisture, content, and weight, and (3) meet quality specifications (Allais et al. 2007a). Operators are subject to the temporal demands imposed by the process and often there is time pressure. An important source of complexity poses challenges for operators: natural variations in the products and their interactions with environmental factors. However, often there is little that operators can do to deal with them, and often they do not even know them.

3.4.3 Integration

The two domains differ in the challenges operators need to face. In the process industries, they have to deal with information overload, while in discrete processing they do not. One reason is that in the process industries process control relies on the supervision of a large, distributed system by monitoring data from different sources, while in discrete processing the work is local, restricted to one or a few production steps, and based on direct observation. A similar difference between the domains is the need to form mental models and make accurate predictions. In the process industries, this is essential due to the complex interactions between process parameters and variability of processes. In discrete processing, some features of complexity are absent (e.g., time delays) but complex interactions of product characteristics and environmental factors would also make it beneficial to form adequate mental models. However, information is absent about many of them, and operators do not receive sufficient training to perform cognitively demanding tasks.

4 Conclusion

Operating a process or processing plant is impossible without operator involvement, but the roles of operators differ between the domains. In the process industries, operators are needed because complex interactions between process parameters and variations in the processing context call for flexible adaptation (Hollnagel 2012). In discrete processing, operators are needed because the same faults re-occur and humans can develop strategies based on experience (Allais et al. 2007b). Thus, operators are valuable because situations are different in the process industries and because situations are similar in discrete processing. Still, in discrete processing there is little focus on operator competencies. Operators perform stereotypical tasks, and little is done to foster an understanding of the process or involve them in the diagnosis of faults. Presumably, some of this can be attributed to characteristics of the technical systems per se. For instance, in discrete processing it is not necessary to make choices between different processing strategies. Thus, in many ways operating a discrete processing plant is less demanding. However, the presence of differences in operator qualification only indicates that it is possible, not that it is good. Discrete processing might also benefit from giving more information, training, and autonomy to operators, and thus making it possible for them to assume a more active role in enhancing the functioning of a plant.

4.1 Involving operators

Approaches to involving operators are manifold, and should span the entire organization. A prominent approach is the Japanese Kaizen concept (Imai 1986). Kaizen means “change for the better” and describes a continuous and incremental improvement involving all employees, from the CEO to the machine operator. Kaizen encompasses several forms of participation, encouraging employees to contribute to their company’s development. There are different ways of implementing Kaizen, and these ways largely vary across companies (Brunet and New 2003). Kaizen activities include quality, safety, productive maintenance, self-management, or labour union activities, and many Kaizen targets and activities are chosen by work teams that form autonomous units. The Kaizen concept does not assume that improvement necessarily goes along with performance increases, which often cannot be measured precisely. Instead, many Kaizen activities target non-performance aspects such as safety, health, or the environment. However, a successful adoption of Kaizen presupposes that there is something in it for the employee, and the demands and compensation for Kaizen activities should be in balance.

Another approach to increasing operator autonomy that addresses the requirements of underspecified, complex systems is the implementation of flexible routines (Grote 2015; Grote et al. 2009). Besides fixed action rules (e.g., SOPs) that specify detailed procedures in a step-by-step manner, process rules can provide guidance for selecting appropriate courses of action, and goal rules can define what goals to achieve but grant operators freedom in selecting the means. Flexible routines are most appropriate when the system calls for situation-specific adaptation in situations that could not be foreseen during design. Thus, they are promising in domains such as the process industries and discrete processing where flexible operator intervention is required. For instance, while in a chocolate processing plant it is impossible to specify how exactly all variations in the chocolate will affect the packaging process, operators can be instructed to monitor the incoming chocolate with regard to parameters such as shape or softness, and adjust the process accordingly.

Evidence for the benefits of giving more autonomy to operators stems from research on operator empowerment. For instance, in a company that produces photographic paper and film, enabling operators to solve faults by themselves increased the time machines were in operation by 6.3%, which corresponds to a production gain of £125,000 per year (Leach et al. 2003). Similarly, handing a greater variety of tasks to operators of CNC machines reduced machine downtime by more than 80%, resulting in a decrease from 150 to only 26 min per shift (Jackson and Wall 1991). Analyses of fault rates and durations revealed that this change can be attributed to increases in proactive control: Operators learned to run the process in ways that prevent faults in the first place. There are three underlying mechanisms by which operator involvement enhances performance (Wall et al. 2002): First, operators can apply their knowledge and use their experience. Second, they can develop their knowledge by learning about the machines, enhancing their skills, and forming more differentiated cognitive structures. Third, they can develop a more proactive orientation by adopting a broader perspective and increasing their personal initiative.

A frequently voiced concern related to higher operator autonomy is that operators might perform inappropriate actions and thereby reduce the system's productivity, or even cause faults and accidents. It is important to note that autonomy needs to go hand in hand with measures for operator support: It is not enough to simply allow operators to act more autonomously, they also need to know how. What can be done to support operators in selecting appropriate actions? At first glance, the present operator tasks and qualification in discrete processing might suggest a direct support of action execution: telling operators what to do in case of a problem, as explicitly as possible, and eliminating the need to think. In fact, a lot of contemporary research on the application of new assistance technologies follows this approach, for instance by using augmented reality to provide detailed instructions (e.g., Tatić and Tešić 2017). Although this approach can be beneficial in some contexts, for instance when pre-defined procedures need to be carried out quickly, it also has some serious shortcomings. Besides not making full use of human potential, automating decision making and action selection increases the risk of automation bias, an uncritical adoption of suggestions from automated decision aids, and they do not support an understanding of situations (Onnasch et al. 2014; Parasuraman and Manzey 2010).

4.2 Resilience engineering and joint cognitive systems

A fruitful theoretical approach that can inform the appropriate involvement of operators is resilience engineering (Hollnagel et al. 2011, 2006; Vanderhaegen 2017). Resilience denotes the ability of a system to adjust its functioning in the presence of changes and disturbances so that it can sustain its performance even under unexpected conditions. In order to be resilient, a system must be able to learn from past events, respond in a flexible manner, monitor short-term developments and threats, and anticipate long-term threats and opportunities. Dedicated methods have been proposed to analyze and enhance the resilience of organizations (Hollnagel 2011). Especially the last resilience activity, anticipation, is a challenge in domains like the process industries and discrete processing, because both are underspecified and thus not all situations can be anticipated beforehand. Thus, for an underspecified system to be resilient, technology and humans must be treated as a joint cognitive system (Hollnagel and Woods 1983), and decision making should be a cooperative activity involving the designer, the technical system, and the operator (Rasmussen and Goodstein 1987): As designers cannot possibly anticipate all future situations, they should provide the means for operators to act as their extended arm on-site, enabling operators and the technical system to cooperate on the same sub-goals. However, this is possible only when the system makes its goals and decision background explicit (i.e., makes its conceptual model available to operators), which includes providing top-down information on design decisions and the reasons behind them. For instance, if operators understand why a safety function is in place, they are less likely to work against it. Thus, system design should foster a shared understanding of the problem space, so that the automated and human agents can act as a team.

But how can technical systems become team players? Inspiration can be drawn from the way human team players behave (Christoffersen and Woods 2002; Klein et al. 2004). Most importantly, team players are transparent and directable: They make it possible for the other partner to observe and understand what they are doing, and they allow their actions to be influenced by the partner. These concepts can be transferred to human–machine cooperation, which is in contrast with many contemporary approaches to automation that aim at making the technical system "invisible", silently adjusting its mode of operation to the situation without requiring the operator to be aware of these changes. However, it is a misconception to think that more highly automated systems should communicate less (Borst et al. 2015). To specify how to design cooperative systems in practice, we need to ask what is required to enable cognitive functions such as situation analysis and evaluation. Ecological interface design (Rasmussen 1999; Vicente and Rasmussen 1992) provides a number of promising methods. In short, it maps the relevant relations in a domain to graphical relations in the interface as emergent features (Bennett 2017). While this approach has successfully been applied in the process industries (Jamieson 2007), it has not been transferred to discrete processing so far. The complex interactions of environmental influences imply that such transfer is promising. Moreover, cooperative human–machine systems for discrete processing should make use of a specific potential of operators in this domain: accumulated experience in the handling of faults. This calls for assistance concepts such as case-based reasoning that store previous instances and make them available when a similar situation occurs (Kolodner 1993; Lopez de Mantaras et al. 2005). Conversational case-based reasoning can help to establish a joint understanding of system states via human–machine dialogues (Aha et al. 2001; Aha and McSherry 2006; McSherry 2005).

4.3 Summary and future directions

Taken together, system characteristics determine the cognitive demands to be faced by operators, and in turn operator knowledge and strategies affect system performance. While this general notion has been common sense in the Human Factors community for decades, there has been little research on the comparison of different systems to specify how their specific characteristics give rise to differences in operator tasks. The present article took a first step by providing a detailed comparison of two production systems to derive an understanding of the resulting differences in cognitive demands. Future work should extend this approach in three ways. First, it should include a wider variety of production systems that pose different challenges for operators. For instance, it would be interesting to contrast discrete processing and car manufacturing, because despite some striking surface similarities (e.g., both domains use linear systems to assemble different parts of discrete, three-dimensional objects), there are profound differences between them (e.g., in car manufacturing environmental factors are less influential and production runs much slower, but for each item different specifications need to be met). Second, instead of focusing on a domain as a whole, future cross-domain comparisons could use specific cognitive functions as their unit of analysis. For instance, it would be interesting to investigate how monitoring activities differ between the process industries and air traffic control, or how hypotheses generation and testing during fault diagnosis differ between the process industries, car mechatronics, and medicine. In-depth comparisons of such cognitive functions between domains could enhance our understanding of the associated knowledge requirements and means for support. Third, it should be investigated how new technologies associated with digitalization affect operators in different production systems. Such comparisons should build on the specific challenges faced by operators in today's systems, asking how the same technologies can be used to support operators in different systems, and how different applications of these technologies could lead to specific benefits in different systems. For instance, while OPC UA and semantic web technologies might help to make more information available to operators in discrete processing, they could aid operators to better integrate and contextualize the available information in the process industries. In any case, cross-domain comparisons are a promising avenue for future interdisciplinary research.

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