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Methods to assess and manage process safety in digitalized process system

CHAPTER ONE

Opportunities and threats to process safety in digitalized process systems—An overview

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1. Definition of digital process, digitalization, and safety

Several developments in the process industry, such as optimal use of energy, more complex processes and process conditions, and larger flexibility for product adaptation, with a work force that is more mobile, ask for a higher degree of automation. To adapt to this change and ensure production safety, digital technologies provide a potential way to improve production efficiency and reduce the likelihood and severity of industrial accidents.

The first push for digital computing in the process industry came in 1949 through IBM's industrial computing seminars (Lee, Cameron, &

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Hassall, 2019). The exponential increases in computing power and software development over the past 70 years have been the mainstay of the development of high-fidelity dynamic modeling of entire process plants (Lee et al., 2019). Fig. 1 shows the main development over the last 80 years.

Digital technologies, which are the bread and butter of Industry 4.0, have been used in many fields such as ecology, economy, engineering, and process system (Single, Schmidt, & Denecke, 2019). A clear definition of digital terms is the first step in determining its opportunities and threats in process systems.

Digital process refers to the basic process of transforming much complex and changeable information of a whole system into numbers and data that can be measured and then using these numbers and data to build an appropriate digital model, introducing them into the internal computer for unified processing (Porthin, Liinasuo, & Kling, 2020). Several authors have expressed their views in this regard in the available literature. However, there is no accepted definition in the academic community so far. There is a good example in process safety to describe the digital process. Single et al. (2019) developed an "semi-automated HAZOP" system to support a HAZOP team to identify potential hazards of a process plant. The information of Process Flow Diagrams (PFDs) and Piping and Instrumentation Diagrams (P&IDs) is exacted and used to represent the process plant. The nodes in PFDs and P&IDs can be modeled by a specific modeling language and a graphical editor. In the light of this, deviations in process variables can be automatically applied and propagated through the process system, detecting potential faults and hazardous events by employing inference methods. In this process, all information, including the information of the process plant and expert knowledge, is transformed into data processed by computers.

Digitization or *digitalization* is defined as the integration of digital technologies in process operations for greater efficiency and increased product quality (Kayikci, 2018; Khan, Amyotte, & Adedigba, 2021; Vaidya, Ambad, & Bhosle, 2018). Digitalization generally means encoding various information (e.g., images, voices, videos, data, etc.) into zeros and ones for better storage, processing, and transmission of information (Khan et al., 2021). The digitalization process comprises the increased use of robotics, automation solutions, and computerization, reducing costs, improving efficiency and productivity, and responding flexibly to changes.

The digitalization in process industries consists of two main parts: (i) physical digitalization (i.e., automation of equipment, holistic simulation

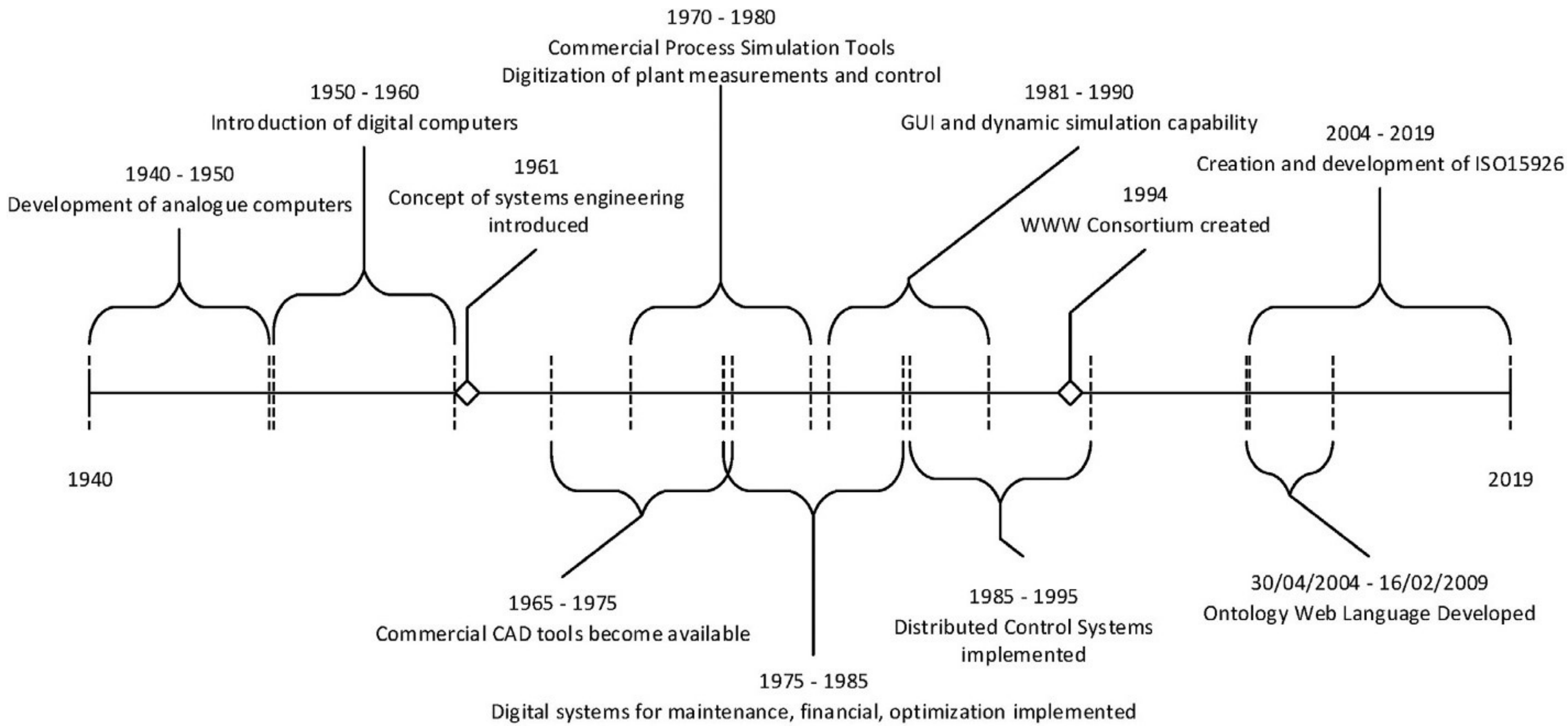

Fig. 1 The development of digitalization in process systems. *Adapted from Lee, J., Cameron, I., & Hassall, M. (2019). Improving process safety: What roles for Digitalization and Industry 4.0?* Process Safety and Environmental Protection, 132, *325–339. doi:10.1016/j.psep.2019.10.021.*

of process systems), (ii) information digitalization (i.e., automation of data collection, processing, and analysis). In the field of process safety, the latter is of greater interest (Lee et al., 2019). The essence of digitalization is to use the abundant data in systems to solve the uncertainty of complex systems. Digitalization enables digital twin, which focuses on the simulation of the overall system to optimize the system structure and verify the effectiveness of existing operating strategies, and collecting, storing, and processing a large amount of monitoring data and production data generated in systems. The main reasons for the growing interest in digitalization are exponential growth in technology development and the fact that data is becoming richer from more sources, real-time with higher data rates, more complex, and more useful.

Digitalization depends on data, and data relies on effective collection, and for reliable use, data should be keept cybersecure, data preparation and effective analysis is required to distil information from them, and in the end, their value would show up by useful application. The analysis focuses on identifying problems and analyzing them based on data and the main reasons behind the generation of such data to monitor the operations and status of process systems and develop strategies and measures for optimization.

Safety in the process industry can be defined as the ability or state of a system to be free from undesired accident risk during the production process (e.g., Hollnagel, 2008). Safety and risk are closely linked. Risk is a composite measure of the probability of an undesired accident and the corresponding consequences. From a conceptual point of view, reducing the accidents' probability and consequence can decrease sytem risk which will improve systems' safety. Early warning (Chang, Khan, & Ahmed, 2011; Schmitz, Swuste, Reniers, & van Nunen, 2020), fault detection and diagnosis (Fazai, Mansouri, Abodayeh, Nounou, & Nounou, 2019; Kopbayev, Faisal, Yang, & Halim, 2022), and safety barriers (e.g., physical barriers and non-physical barriers) can be used to improve the safety of process systems.

2. Brief history of process safety and reasons why digitalization can support process safety

2.1 A brief history of process safety

Process systems, and, in particular, chemical ones store and process a large amount of hazardous materials, which by explosion blast, radiant heat, or toxic substance exposure may lead to casualties, property damages, and ecological pollution (Abbassi, Khan, & Garaniya, 2015; Benson, Dimopoulos, & Argyropoulos, 2021; Khan, Wang, & Yang, 2016; Sun, Haiqing, Yang, & Reniers, 2021). Quite a few compilations of accidents that occurred are available, e.g., Marsh, 100 Largest Losses in the Hydrocarbon industry 1974–2019 (Marsh, 2020), while several countries maintain accident data bases, e.g., in Europe the JRC eMARS database. As a typical accident the Amuay refinery disaster in Venezuela can be mentioned causing more than 50 people dead, over 100 people injured, and about 1600 buildings destroyed, resulting in $1 billion in economic loss (Mishra, Wehrstedt, & Krebs, 2014). There have been many more, some more serious, others less.

Process safety plays a critical role in safety operations during production processes. It is identified as an integral part of process development and manufacturing rather than being viewed as an "add-on" to the process (Gibson, 1999). However, safety was not a high priority in the 1940s. At that time, the full-time safety worker were older foremen, retired army officers, and men (no women then) with non-technical backgrounds and experience (Kletz, 2012, see also, Swuste, Van Gulijk, & Zwaard, 2010). At British industrial pioneer Imperial Chemical Industries (ICI), in the late 1960s, only after several major safety incidents in a row, management decided that the safety work should be done by people with relevant knowledge and technology. In 1963, the method of Hazard and Operability (HAZOP) study started its development at ICI to identify the hazards and determine the potential equipment failures (Kletz, 1999, 2012). It is worth noting that late Trevor Kletz was the promotor of HAZOP within ICI and beyond. Besides, he advised and trained workers to conduct the HAZOP process. Since then, although the scale of process industries has doubled in the 1970s, the rate of fatal accidents in the process system has dropped significantly (Kletz, 1999), which can be seen in Fig. 2.

The origin of the term "process safety" and its evolution is related to the major accidents that occurred between 1960 and 1990 as a result of rapid industrialization and technological developments (Khan, Rathnayaka, & Ahmed, 2015). In other words, the driving force behind the movement to foster process safety and to regulate the industry is the unwavering occurrence of major accidents. For example, the Flixborough aerosol cloud explosion accident in the UK in June 1974 led to the death of 28 workers and injured 36 staff, besides destroying the plant and damaging nearby residential area. This disaster promoted in the same year the creation of the Advisory Committee on Major Hazards by the Health and Safety

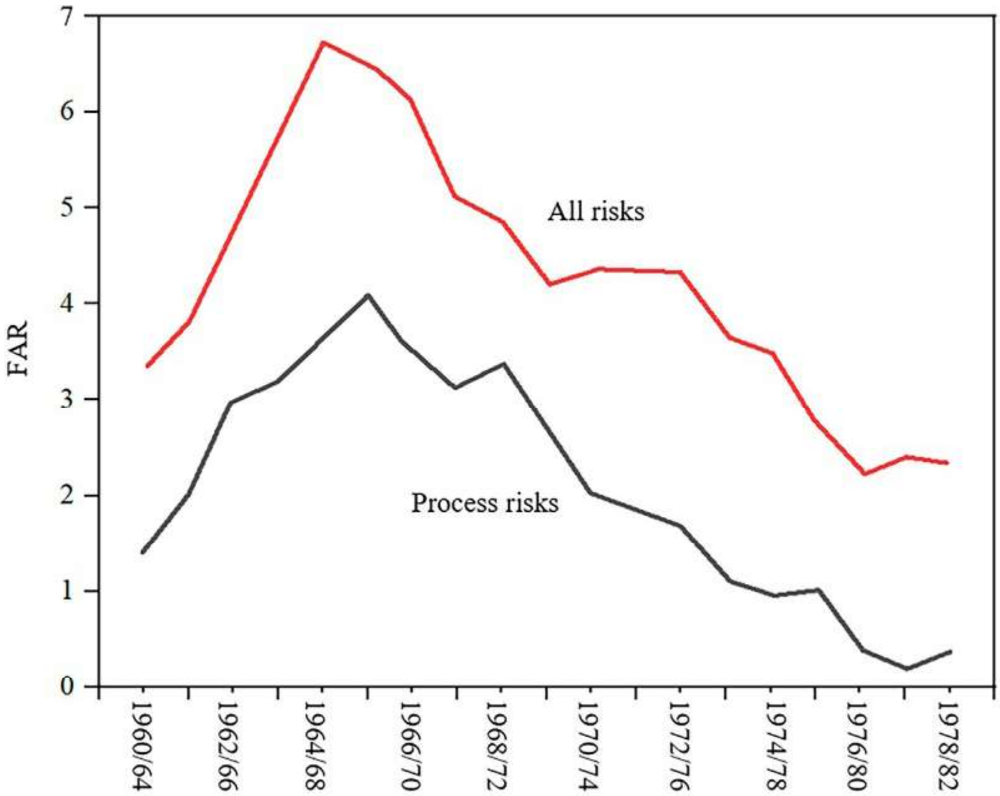

Fig. 2 Fatal accident rate from 1960 to 1982. *Adapted from Kletz, T. (2012). The history of process safety.* Journal of Loss Prevention in the Process Industries, 25*, 763–765. doi:10.1016/j.jlp.2012.03.011.*

Committee in the United Kingdom, which itself was based on Health and Safety at Work etc. Act 1974.

Those developments were followed in continental Europe and the United States. But the engineering associations became already active earlier by organizing symposia to exchange experiences and to learn from each other. The earliest are the AIChE Loss Prevention symposia in the United States starting in 1967, while the IChemE 1971 Major Loss Prevention in Newcastle UK became the initiating gathering for the EFCE Loss Prevention symposia in Europe with the first one in 1974. In Table 1 a number of shocking accidents have been listed, which gave rise to changes in thinking and approaches to safety.

Economically the process industry was booming as the demand for its products grew as again seen in Japan, later in the early 1990s in the Middle-East followed by many Asian countries, notably China, and India. The hazardous nature of the substances (flammable, explosive, toxic) in the system makes it possible to cause severe consequences in the event of an accident. Especially, for toxic materials, in the event of a leakage, the consequences would be unacceptable. For instance, after the TCDD spreading

Table 1 The development of process safety influenced by major incidents.

Accident	Type	Time	Number of death and injury	Corresponding organization	Formed regulation	Reference
Flixborough, United Kingdom	Explosion	1974	28, 36	Advisory Committee on Major Hazards	New UK regulations for the control of industrial major accident hazards (CIMAH)	Mannan, Chowdhury, and Reyes-Valdes (2012)
Seveso, Italy	Loss of containment	1976	Severe pollution	The European Chemical Industry Council	Seveso I, II, and III	Hay (1977)
Bhopal, India	Loss of containment	1984	3000–20,000, hundreds of thousands were injured	Center for Chemical Process Safety (CCPS)	Environmental Policy Act; Air Act; Hazardous Waste (Management and Handling) Rules; Public Liability Insurance Act; Environmental Protection (Second Amendment) Rules	Mannan et al. (2005)
Pipe Alpha, United Kingdom	Loss of containment	1988	167, –	–	Safety case regulations; Permit-to-work system	Mannan et al. (2005)
Exxon Valdez Spill, United States	Loss of containment	1989	Severe pollution	–	Oil pollution Act	Khan (2007)

Continued

Table 1 The development of process safety influenced by major incidents.—cont'd

Accident	Type	Time	Number of death and injury	Corresponding organization	Formed regulation	Reference
Phillips 66, United States	Explosion	1989	23, hundreds	Chemical Safety and Hazard Investigation Board (CSB); Mary Kay O'Connor Process Safety Center (MKOPSC)	Clean Air Act Amendments, with the OSHA PSM regulation and later the RMP rule of EPA	Mannan et al. (2012)
BP Texas City, United States	Fires and explosions	2005	15, 200	Occupational Safety and Health Administration (OSHA)	Revision of the American Petroleum Institute's (API's) Recommended Practice (RP) 752	Kaszniak and Holmstrom (2008)
T2 Explosion, United States	Explosion	2007	4, 32	Accreditation Board for Engineering and Technology	Relevant evaluation criteria	Theis (2014)
Deepwater Horizon, United States	Explosion	2010	11, –	Bureau of Safety and Environmental Enforcement (BSEE); Bureau of Ocean Energy Management; Center for Offshore Safety; Ocean Energy Safety Institute	Relevant management criteria	Skogdalen, Khorsandi, and Vinnem (2012)
West Fertilizer Explosion, United States	Explosion	2013	15, 160	–	President Obama's Executive order to screen/improve regulation	Mannan, Reyes-Valdes, Jian, Tanim, and Ahammad (2016)

Seveso runaway accident, to avoid further dioxin contamination, more than 80,000 animals had to be exterminated, censored thousands of people in their activities, and allowed abortions based on mothers' decisions. To avoid the occurrence of major accidents, institutions were developed and regulations made. It can be seen in Table 1 that each major incident has facilitated the development of process safety, including promoting the establishment of relevant institutions and laws and regulations.

The focus of research on process safety has varied over time as systems and laws, and regulations have evolved. As mentioned above, in the 1960s, safety was not a concern until major accidents occurred. In order to prevent accidents, people with technical background were tasked to carry out relevant work. In the beginning, process safety focused on technical problems, which can be seen in Fig. 3. Accidents were seen as being caused by equipment failure. In quite a few cases the mechanism of a cause chain resulting in a severe consequence was not clear. Type denotations, such as reactor run-away and vapor cloud explosion, had to be invented yet. However, the call for proactive approach became stronger and Trevor Kletz's HAZOP, to identify already at the design stage potential technical failures of process systems became famous (Gowland, 2012). Also around 1974 following the example of the nuclear power industry, the concept of risk asessment emerged with the Canvey Island (UK, Canvey, 1978) and Rotterdam Rijnmond (Nl, COVO, 1982) studies. These studies recognized the problem of lack of knowledge on equipment failure data,

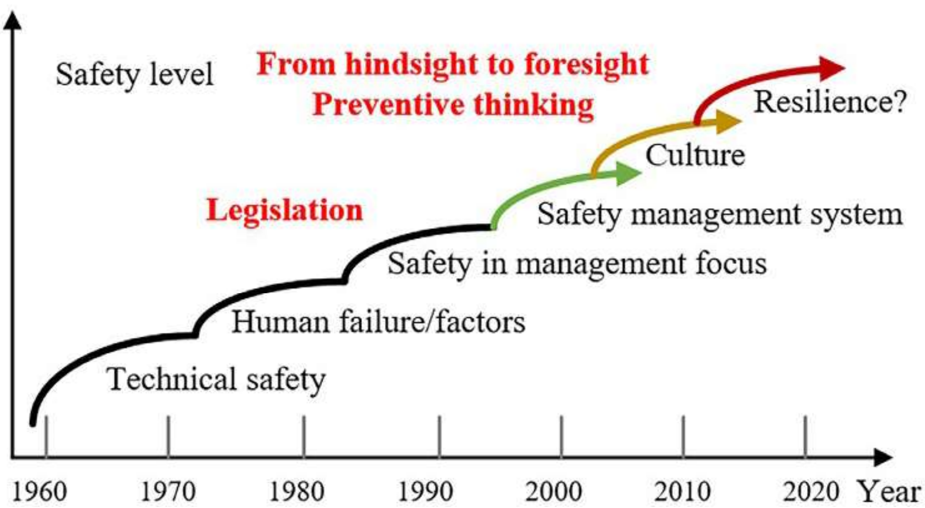

Fig. 3 Major contributions to the evolution of process safety presented in 1995 at the 8th European Loss Prevention symposium in Antwerp by Koos Visser, process safety pioneer at Shell, and since then stepwise expanded by Hans Pasman (Pasman & Fabiano, 2021).

consequence analysis models, and the importance of human factors in the safety performance of the process industry. A wave of activities in the 1980s and 1990s started to gather data by collecting equipment failure ones, by experiments and field trials, to develop models and to expand knowledge. Human factors led to significant developments in management and behavioral sciences, as well as advances in systems and cultural approaches (Khan et al., 2021). In this century, due to better insights and more complex process systems, more attention has been paid to socio-technical system approach, in which human factors, technical factors, and organizational and managerial factors interact. Note that since the Chernobyl nuclear reactor disaster in 1986, safety culture is recognized as important and over the years is taken into account in organizational and managerial factors. The Phillips Petroleum company 1989 dramatic vapor cloud explosion near Houston, US, gave the impetus to US Occupatioal Safety Administration (OSHA) to launch the Process Safety Management (PSM) requirements, which led further to safety management systems (SMS). The effect of these introductions of concepts appeared industry sometimes only many years later (Fig. 3). Nowadays, as digitalization proceeds, process systems belong to the cyber-physical system, which means more focus should be on managing process safety information and communicating these experiences as knowledge. Meanwhile, the impacts of digitalization on process safety require more discussion.

2.2 Why can digitalization support process safety?

To prevent accidents, scholars developed various risk assessment (RA) method variants to reduce the probability of an accident and mitigate accident consequences (Khan, Khan, & Veitch, 2020; Khakzad, 2019; Landucci, Argenti, Cozzani, & Reniers, 2017; Sultana, Anderson, & Haugen, 2019; Yang, 2018). RA plays an essential role in understanding the mechanism of accidents and ensuring system safety. Following Sam Mannan's thougths O'Connor, Pasman, and Rogers (2019) proposed three crucial elements of safety, namely, prevention, mitigation, and response, which can be integrated as a so-called safety triad. These three factors may seem simple, even intuitive. However, reports and investigations of accidents have proven that the main cause of accidents was the lack of these three factors. To determine their effectiveness methods, such as fault and event tree have been devised, which over the years became further developed. An example is bowtie which combines fault and event tree and shows besides scenarios also preventative and protective barriers. For quantitative evaluation of the probabilities of basic events to final major consequences bowties can be easily converted into Bayesian networks (see, e.g., Khakzad, Khan, & Amyotte, 2013). Because there may be interdependency of events and barriers, Ghosh, Ahmed, Khan, and Rusli (2020) utilized copula-based Bayesian network (BN), as well as traditional BN to assess the failure of the multivariable time-dependent system. Sun, Wang, Yang, and Reniers (2020) developed an integrated approach based on the window of opportunity and complex network to evaluate the risk of a process system.

The works described above show the significant progress on RA in process systems. Nevertheless, recurring accidents show that relying on conventional RA alone and following its recommendations is not enough to ensure system safety (Marsh, 2018). Marsh (2018) indicates the losses caused by accidents have not been reduced. In fact, semi-quantitative or quantitative risk assessment is not applied taking all possibilities and parameters into account, and moreover the used models and data contain large uncertainties and the analysts are limited in their knowledge and awareness as, e.g., well described by Rae, Alexander, and McDermid (2014). Nowadays, complex systems, which arise from non-linear interdependencies, are built rapidly to meet people's demand. The ensuing uncertainty, complex interaction, and interdependence between components (e.g., human, technical, and organizational elements) have become new risk factors in the process system.

These changes make it difficult to assess reliability, detect and diagnose faults, and determine the relationship between process parameters and system state. For example, deterioration and corrosion of equipment (such as valves) is a random process influenced by process parameters and "non-equipment factors" such as human factors, technical factors, environmental factors, etc. It is difficult to use the abovementioned traditional RA methods to ensure system safety under those conditions.

Automated and digital systems generate a large amount of data, leading to new opportunities for process safety and asset integrity assessment. Lee et al. (2019) suggest digitalization of chemical process industries could improve the mechanical issues by introducing early warning signaling, corrosion monitoring, remote sensing, increased connectivity, application of predictive models relying on real-time data, and machine learning. Moreover, they suggest digital systems could improve work processes, risk assessment, operator interfaces, and alarm management systems. In addition, digitization benefits from generating digital operational data and replacing manual operations with software that automates data collection, processing, and analysis for effective process monitoring.

Specifically, the benefits of digitalization are mainly reflected in five aspects: productivity, production quality, safety, efficiency, and flexibility (Hole, Hole, & MaFalone-Shaw, 2021). For example, digitalization can reduce labor and save costs. A high degree of automation can increase productivity while ensuring product quality and system safety. Digitalization provides novel and more efficient measures to improve the manufacturing process and safety system (e.g., safety barrier system). In practice, much information on site needs to be recorded by workers and fed back to the control room, which wastes a lot of time recording and feeding back, and increases the probability of human error. It is not conducive to safe and efficient production. Fortunately, digitalization can solve this problem. Besides, digitalization can help to improve control systems, which enables every process of production to be monitored effectively. This ensures the safety of the system and the quality of the product. For example, the boiled-off gas (BOG) is inevitably generated at the LNG receiving terminal during unloading, storage, and delivery. An effective control system can reduce the amount of BOG and thus save energy from liquefied BOG (Animah & Shafiee, 2020).

For processes, safety is a most critical concern. The benefits of digitalization for safety can ensure system safety by performing fault detection and diagnosis, risk assessment, and safety control. Reinartz, Kulahci, and Ole (2021) developed an extensive reference dataset, incorporating repeat simulations of healthy and faulty process data, additional measurements, and multiple magnitudes for all process disturbances. All six production modes of the Tennessee Eastman process (TEP) process control testbed as well as mode transitions and operating points in a region around the modes, are simulated. Besides, fault detection is conducted based on principal component analysis integrated with T^2 and Q charts using average run length as a performance metric to provide an initial benchmark for statistical process monitoring schemes for the presented data. Wu and Zhao (2021) presented a process topology convolutional network (PTCN) approach to conduct fault diagnosis of a chemical process system. The proposed method was validated by experiments on the benchmark Tennessee Eastman process (TEP), and results showed that PTCN improved the fault diagnosis accuracy. Cheded and Doraiswami (2021) developed a comprehensive approach, including model-free (MFA) and model-based (MBA) methods, for fault detection and isolation with in process system. Deng, Han, Cheng, et al. (2022)

proposed a real-time fault detection approach, which comprises space-time compressed matrix (STCM) and Naive Bayes (NB), to realize the fast learning and prediction in chemical process system. Experiments on the TEP show that the proposed approach reduces the sample size and feature size by 75% and 92%, respectively. Bi and Zhao (2021) presented a novel orthogonal self-attentive variational autoencoder (OSAVA) model, which includes orthogonal attention (OA) and variational self-attentive autoencoder (VSAE), to monitor the process system. OA is utilized to extract the correlations between different variables and the temporal dependency among different timesteps; VSAE is trained to detect faults through a reconstruction-based method, which employs self-attention mechanisms to comprehensively consider information from all timesteps and enhance detection performance. Arunthavanathan, Khan, Ahmed, and Imtiaz (2021) developed an early potential fault detection approach, including the Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM), to examine fault symptoms in chemical process systems. The performance of the proposed approach was validated by TEP again and indicated that the proposed method is efficient in finding out potential faults in chemical process systems. This will all be further detailed in Chapter 6.

3. Process safety treated in digitalized process systems

The benefits of digitalization in process systems are the generation of digitized operational data and the replacement of manual process operations with software that allows automated data collection for effective process monitoring (Khan et al., 2021). Digitalization can help systems predict uncertain disruptions, monitor, and control the process of systems, detect and diagnose faults, manage abnormal situations, and process massive amounts of data automatically. Therefore, the productivity, flexibility, and quality of process systems can be enhanced. However, new problems arise when most operations are digitally (e.g., sensor, controller, processor) dependent.

3.1 Human and management errors

The analysis of the causes of the 100 major accidents in the area of onshore oil, gas, and petrochemical from 1996 to 2015 was conducted by Jarvis and Goddard (2017). This study revealed major system failure causes: mechanical failures accounted for 43% of losses; operations, practices, and procedures made up 25%; work control accounted for 21%, etc. The above statistics illustrate the impact of management system failures on accident occurrence. It should be noted that nearly 60% of mechanical failures were due to management issues, such as inadequate inspection programs. Besides, hazard identification is involved in more than half of losses due to human errors.

Even though digitization is beneficial for reducing operators' workload and involvement time, it increases the complexity of human-computer interaction. This is because the screens, displayed data, and buttons in the control room will become more numerous and complex. Moreover, the system generates and automatically processes a large amount of data, and while most decisions are made automatically by the system, the decisions of the people in the control room remain also critical to ensuring the safety of the system. In addition, managers and operators are prone to laxity because they may believe all work can be done by digitalized equipment. Situation awareness, safety awareness, safety culture, management policy, etc., may decrease with the development of digitalization. This observation can be supported by an accident on December 11, 2005, at the Buncefield storage depot in the United Kingdom. The main cause of the overfilling of the gasoline (petrol) storage tank was the failure of the automatic tank measurement system while the control room was manned at the time (Paltrinieri, Øien, & Cozzani, 2012).

3.2 Process monitoring and control

Due to digitalization, equipment, including sensors, indicators, detectors, controllers, and valves of main process parameters (e.g., temperature, pressure, flow rate, etc.), are more automated. This means that fewer devices require human involvement. Although it reduces human errors and time, it lmay loose human as a vital back-up safety barrier. For example, there are also manual detectors in conventional process systems in addition to automatic detectors. When automatic detectors fail, regular manual detection can assist in the prevention of major accidents. However, digitalization may abandon most equipment that requires human involvement, which may increase systems risk if the reliability of the system is not sufficiently increased.

Process monitoring allows for fault detection and diagnosis by monitoring important process parameters, which is beneficial for ensuring system safety. However, relying entirely on automated monitoring cannot fully secure the system. For example, under normal conditions the safety instrumentation system (SIS) is dormant, and it only works when an accident occurs and demands it to function. Although faults can be signaled in part automatically, in particular of the electronics, for this type of equipment, human involvement of inspecting and testing will remain essential.

3.3 Massive data processing

With the process of Industry 4.0, process systems have become more automated and intelligent, which means that monitoring systems, control systems, and operation systems produce massive data (Pasman & Fabiano, 2021). Adequate use of those data is beneficial for early warning, fault detection, diagnosis of the system, etc. However, due to limited time and resources, it is challenging to analyze all of those data. To overcome the challenge, researchers paid more attention to developing a targeted approach to handling massive data. These methods are categorized as the data-driven method.

One of the representative methods among data-driven methods is machine learning. Machine learning consists of two types of methods: unsupervised learning and supervised learning.

Unsupervised learning is relevant when one wants to find out whether the data contain a pattern which at that moment is unknown. The technique includes clustering algorithms (e.g., K-means clustering) and dimension reduction algorithms (e.g., principal component analysis (PCA)). PCA is widely used to reduce the dimensionality of data by exacting the main features from the massive data. Ji, Jiao, Yuan, et al. (2021) employed PCA to analyze high dimensional data to assess the combustion risk of flammable liquids. Li, Hu, Gao, et al. (2021) Li, Jia, Zhang, et al. (2021), Li, Liu, Lin, et al. (2021), Li, Zhang, Khan, and Han (2021), Li, Zhou, and Wang (2021) developed a data-driven model, including PCA, artificial bee colony algorithm (ABC), and support vector regression (SVR). In this model, PCA is employed to reduce the dimension of corrosion influencing factors. The obtained primary components are selected as the input variables of the model. Kopbayev et al. (2022) combined Kernel principal component analysis (kPCA) and deep neural network (DNN) to perform fault detection and diagnosis in process system. In the proposed method, kPCA is used to reduce the dimensionality of the complex data. After this, the processed data is utilized for training DNN for detection and diagnosis. Amin, Khan, Ahmed, and Imtiaz (2021) presented a comprehensive method, including PCA and Bayesian network, for fault diagnosis. Wu, Li, and Li (2021) utilized the Principal Component Analysis (PCA) in combination with Support

Vector Machine (SVM) to classify the fault for complex process systems. The results show that the developed approach is efficient for fault detection and diagnosis. Harrou, Nounou, Nounou, et al. (2013) presented a PCA-based GLR fault detection method to detect faults in different process variables without a process model. Kaced, Kouadri, Baiche, et al. (2021) used the PCA to solve the problem of false alarms in a chemical process.

Supervised learning learns the underlying class distinctions or trends from a training data set. It comprises a classification algorithm and regression algorithm. K Nearest Neighbor is a typical classification method. Besides, classification algorithm includes Decision Tree, Support Vector Machine (SVM), Logistic Regression, Random Forest, etc. depending on whether the problme is linear or not and other. Meanwhile, the regression algorithm comprises Linear Regression, Least Square Regression, Artificial Neural Network (ANN), etc. In process safety, one of the most used methods is ANN. ANN is composed of three parts: neurons, layers, and networks. A typical ANN has three layers, the input layer, hidden layer, and output layer. The basic neurons are connected by weights between the input and hidden layers and the hidden layer and output. Put another way, the connection only exists between layers, and there is no connection within a layer since the information flows in one direction. It can be optimized based on new data and information. Due to these advantages of ANN, it is used in many research domains, such as risk analysis and fault detection and diagnosis. Adedigba, Khan, and Yang (2018) utilized multi-layer perceptron (MLP) and probability analysis to evaluate the safety of the process system. The non-linear relationships among process variables are determined by the MLP. Ayhan and Tokdemir (2019) developed a comprehensive approach, including latent class clustering analysis (LCCA), ANN, and case-based reasoning (CBR), for identifying potential accident scenarios. Sarbayev, Yang, and Wang (2019) utilized ANN to overcome the limitations of FT to quantify the risk of the process system. Li, Hu, et al. (2021), Li, Jia, et al. (2021), Li, Liu, et al. (2021), Li, Zhang, et al. (2021) and Li, Zhou, and Wang (2021) integrated computational fluid dynamics (CFD) with a general regression neural network (GRNN) to evaluate the rescue risk in explosion accidents. Li, Hu, et al. (2021), Li, Jia, et al. (2021), Li, Liu, et al. (2021), Li, Zhang, et al. (2021), and Li, Zhou, and Wang (2021) proposed a hybrid approach, which is composed of KPCA and BRANN, for predicting corrosion degradation of offshore oil pipelines. KPCA is utilized not only for decreasing the dimensionality of the factors affecting pipeline corrosion and for extracting principal features from massive data.

Meanwhile, BRANN is formed as a prediction model. Mamudu, Khan, Zendehboudi, and Adedigba (2021) proposed a comprehensive method, which consists of a multilayer perceptron–artificial neural network (ANN) and BN, to assess the risk of the system. Many of these methods will appear in several chapters of this volume.

Although massive data processing methods have undergone significant improvements globally over the past couple of decades, this has not translated into a substantial reduction in major accidents in process industries. The inherent characteristics of industrial system data create numerous challenges for effective process fault diagnosis (Khan et al., 2021). Those data are complex, nonlinear, highly time-variant, and non Gaussian in distribution. Therefore, it is also a challenge to extract important information from those complex data and to accurately perform fault detection and diagnosis.

3.4 Cyber-attacks

The rapid development of digitalization has brought about a strong increase of digitized process systems full of sensors, processing electronics, and often connected wireless via IIoT (the industrial internet of things), which inevitably creates new hazards and risks, like internet cyber-attacks. According to different attack motivations, attackers, hence hackers, can be divided into four categories: terrorists motivated by political gain and revenge, activists inspired by rebellion, disgruntled employees and contractors motivated by money and revenge, and criminals motivated by money (Iaiani, Tugnoli, Bonvicini, & Cozzani, 2021). Cyber-attacks are targeted, which means that they can bring about serious consequences. Moreover, due to the high level of automation and the ongoing digital transition (e.g., increased use of automated sensors, detectors, controllers, diagnostics, digital communications, wireless connections, the interconnection between control and safety instrumented systems, connections to external networks), incidents caused by cyber-attack are more frequent than before. The cybersecurity-related incidents in different industrial sectors are shown in Fig. 4. It is worth noting that the incidents in chemical and petrochemical account for 54.87%. This is because the cyber-attacks on chemical and petrochemical systems can result in severe impacts, which means it is more attractive for cyber-attacks than other areas. Therefore, there is a need to address the impact of cyber attacks on industrial sector facilities (such as nuclear power plants, water and food plants, chemical plants and oil refineries).

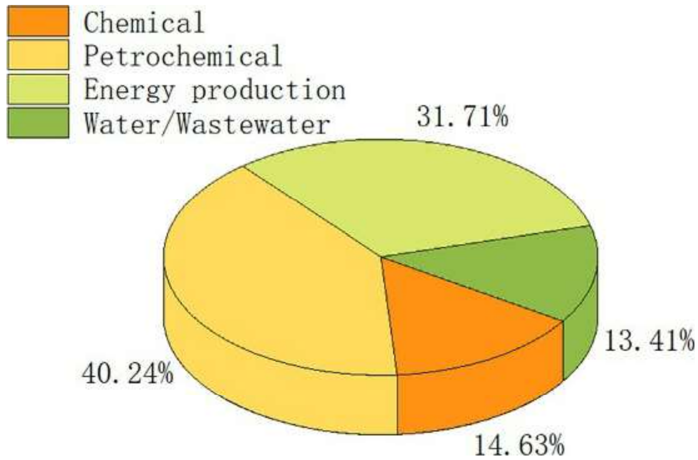

Fig. 4 The cybersecurity-related incidents in different industrial sectors.

4. Purpose and organization of this MCPS Volume 6

This book is the sixth volume of the *Methods in Chemical Process Safety* book series. This volume aims to provide state-of-art progress of digitalization and corresponding opportunities and threats in process safety. Chapter "State-of-the-art in process safety and digital system" by Amin et al. will do that in more detail. Chapter "Data-driven approaches: Use of digitized operational data in process safety" by Bai et al. details the application of data-driven approaches to process safety, including process monitoring, dynamic and operational risk assessment, and reliability modeling/predictive maintenance. Chapter "Industry 4.0 based process data analytics platform" by Wanasinghe et al. briefly presents Industry 4.0 based process data analytics platform, comprising data acquisition, IoT technologies, machine learning, and big data. Chapter "Digital process safety management" by Slezak et al. summarizes specific details on available process safety management (PSM) and safety management system. It discusses the advantages and disadvantages of digital (PSM and SMS). Chapter "Statistical approaches and artificial neural networks for process monitoring" by Alauddin et al. discusses statistical approaches and artificial neural networks for process monitoring for fault detection and diagnosis. Chapter "Alarm management techniques to improve process safety" by Yang et al. will be on alarm management, which in many cases is the start of abnormal situation management in digitalized process systems. It provides the details of conventional and advanced alarm system, including alarm signal processing, alarm prioritization and control, and alarm response procedures. Chapter "Performance evaluation of digitalized safety barriers" by

Zhang and Liu will be on smart safety instrumented system (SIS) and performance evaluation of digitalized safety barriers. Chapter "Dynamic operational risk assessment in process safety management" by Li et al. explains advantages of dynamic operational risk assessment in process safety management. Besides, in this chapter the methods of risk assessment and dynamic risk assessment are briefly discussed. Next, in chapter "Risk of cascading effects in digitalized process systems" by Iaiani et al. the risk of cascading effects and uncertainty modeling in risk assessment of digitalized process systems are provided. Chapter "Uncertainty modeling in risk assessment of digitalized process systems" by Yazdi et al. treats the uncertainty in risk assessment outcomes. Chapter "Human factors in digitalized process operations" by Srinivasan et al. describes the effect of human factors in digitalized process operations. Chapter "Safety assessment of complex socio-technical systems" by Paltrinieri explains the safety assessment of complex socio-technical systems, while chapter "Security of digitalized process systems" by El-Kady et al. will provide the state of play of security measures in digitalized process systems. Chapter "Integrated dynamic risk management in process plants" by Taleb-Berrouane and Pasman discusses aspects of the integrated dynamic risk management in process plants, including safety and security interactions and economic aspects. A more detailed treatment of application of digital twins in process safety management is provided in chapter "Use of digital twins for process safety management" by Keprate and Bagalkot. Chapter "Resilience analysis of digitalized process systems" by Yarveisy et al. discusses the details of resilience analysis of digitalized process systems, comprising various definitions and evolving methods. Finally, chapter "Risk assessment in Industry 4.0" by Amin and Khan shows and summarizes risk analysis in the Industry 4.0 time frame and concludes this volume.

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