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Research
Smart Process Manufacturing: Deep Integration of AI and Process Manufacturing—Perspective

Opportunities and Challenges of Artificial Intelligence for Green Manufacturing in the Process Industry

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A B S T R A C T

Smart manufacturing is critical in improving the quality of the process industry. In smart manufacturing, there is a trend to incorporate different kinds of new-generation information technologies into process-safety analysis. At present, green manufacturing is facing major obstacles related to safety management, due to the usage of large amounts of hazardous chemicals, resulting in spatial inhomogeneity of chemical industrial processes and increasingly stringent safety and environmental regulations. Emerging information technologies such as artificial intelligence (AI) are quite promising as a means of overcoming these difficulties. Based on state-of-the-art AI methods and the complex safety relations in the process industry, we identify and discuss several technical challenges associated with process safety: ① knowledge acquisition with scarce labels for process safety; ② knowledge-based reasoning for process safety; ③ accurate fusion of heterogeneous data from various sources; and ④ effective learning for dynamic risk assessment and aided decision-making. Current and future works are also discussed in this context.

1. Introduction

The process industry, which is a subclass of the raw material industry, is important for national economies. After decades of development, the process industry has made significant progress in China, making China one of the largest manufacturing countries [1,2]. However, compared with developed countries, China's process industry now urgently requires intelligent management and marketing technologies to increase the utilization rate of raw materials, while establishing more functional environmental and safety management systems. This issue has drawn strong academic attention, and much progress has been made in related research fields.

Recently, the dramatic growth of new-generation information technologies has prompted several countries to seek new strategies for industrial revolution [3] (Fig. 1). The United States has launched Smart Process Manufacturing [4], which aims at industrial upgrades and transformation. Germany has proposed the strategic concept of Industry 4.0 [3], which focuses on the integration of information technology into manufacturing. The United Kingdom (UK), France, and Japan have respectively announced the UK 2050 strategy, the New Industrial France program, and the Society 5.0 strategy. In this context, China's government has put forward New Generation of Artificial Intelligence Development Plan for the realization of the "new industrial revolution" [5]. The New Generation of Artificial Intelligence Development Plan concentrates on "innovative, coordinative, green, open, and shared development," which is capable of promoting intelligent manufacturing.

In the context of the national strategies addressing the new industrial revolution, smart manufacturing is the current trend in the process industry, with green manufacturing as one of its indispensable components [1,6–8]. Green manufacturing focuses on high-level efficiency and safety, which reflects the need for stricter environmental policies and better accident prevention. Green manufacturing can be realized with three main objectives in mind: ① the reduction of energy consumption and pollutant emissions; ② life-cycle process-safety monitoring and risk control; and ③ environmental footprint monitoring and evaluation. Thus far, there is no well-understood way to achieve these objectives.

Artificial intelligence (AI) [9], which is a comprehensive frontier technology, has attracted extensive attention worldwide for its extraordinary performance in AlphaGo [10]. Today, AI is regarded as one of the world's three most advanced technologies and has

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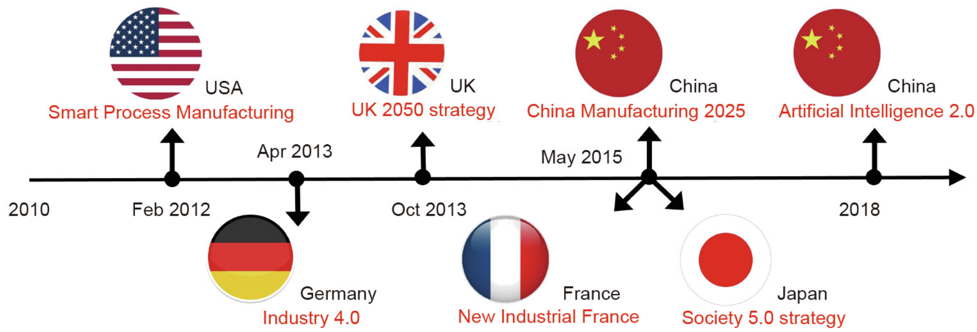

Fig. 1. Governmental programs proposed by several countries to address the new industrial revolution.

remarkably affected several fields, including computer vision, natural language processing, and robotics. Moreover, it is widely believed that AI is critical for smart manufacturing.

In this paper, the challenges associated with green manufacturing in the process industry are discussed in detail. AI plays an important role in improving process-safety management and increasing efficiency through the intelligent utilization of materials and energy consumption. The remainder of this paper introduces the existing technical challenges of integrating AI into the process industry [11]. The main contributions of this paper are as follows:

(1) The current status of process safety in China's petrochemical industry is summarized and major problems for achieving green manufacturing in the process industry are identified; these provide significant guidelines for green manufacturing.

(2) In view of the current status and major problems of China's petrochemical industry, our perspective is offered: AI is the core technology for realizing green manufacturing. Several techniques are available to address these major problems in order to achieve green manufacturing, including knowledge graphs, Bayesian networks, and deep learning.

(3) Considering the complex safety relationship between the process industry and the characteristics of the process industry, several technical challenges are put forward regarding the application of knowledge graphs in the process industry. These challenges may attract the interest of future researchers.

The remainder of this paper is organized as follows. The current status and problems of green manufacturing in the process industry are described in Section 2. Potential AI techniques with relevance to green manufacturing are described in Section 3. Several technical challenges related to AI in green manufacturing are presented in Section 4. Recent progress and future perspectives are discussed in Section 5, followed by conclusions and an outlook in the last section.

2. Current status and problems of green manufacturing

2.1. Green manufacturing

It is widely acknowledged that the manufacturing industry has experienced three industrial revolutions and is now undergoing a fourth (Fig. 2). Each of the first three revolutions tremendously contributed to productivity and economic development [12]. Thus, it is widely believed that the fourth revolution, termed "smart manufacturing," will also make such contributions.

Petroleum and chemicals are significant components of the process industry. According to the National Bureau of Statistics of the People's Republic of China, the petrochemical industry has become one of the pillar industries of China's national economy, contributing 12% of the total industrial output in 2017. Along with tremendous contributions to the development of China's national economy, the petrochemical industry has brought about negative effects on both public health and environmental safety, due to long-term pollution effects and frequent accidents [13]. In the information era, industrial accidents are reported and spread worldwide through various news channels and social media, making the public well-informed and concerned. This motivates the government to establish stricter standards and regulations for the corresponding industry, which increases the demand for green manufacturing. Recent major accidents such as the Xiangshui

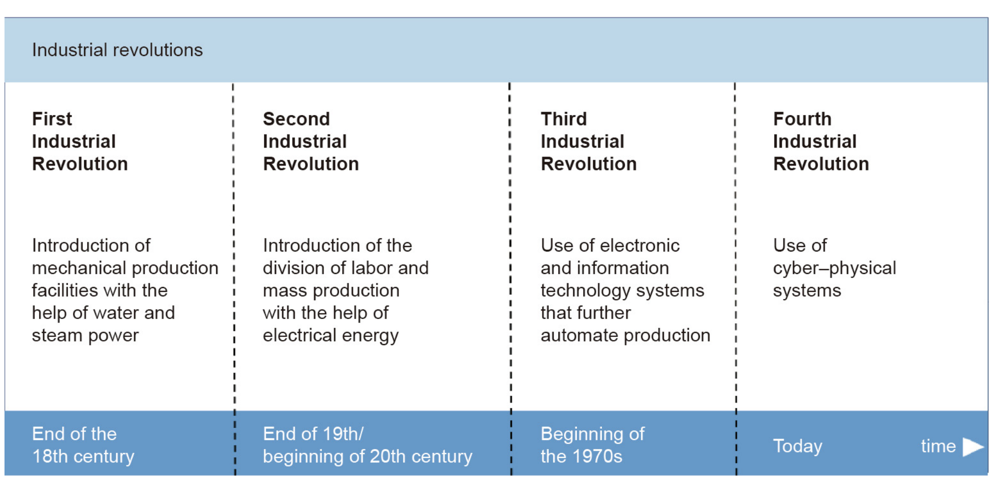

Fig. 2. Four industrial revolutions.

"3·21" chemical plant explosion accident, the Tianjin Port "8·12" fire and explosion accident [14], and the Qingdao "11·22" crude oil leaking and explosion accident [15] not only caused serious casualties, tremendous economic losses, and severe environmental impacts, but also had a negative effect on the development of the petroleum and chemical industry. The government of Jiangsu Province plans to close more than half of the existing chemical enterprises by 2022.

In addition to process safety [16], the environmental impact of the petrochemical industry—both the short-term impact and the long-term influence—is of concern. In comparison with discrete manufacturing, the process industry in China is characterized by low material and energy efficiency, and serious pollution problems. Given the scale of the process industry in China's national economy, there is an urgent need to reduce energy consumption and process emissions under the increasingly restrictive requirements of environmental protection.

Green manufacturing [17,18] is regarded as a solution that can achieve process safety, energy consumption, and emission reduction. It aims to track safety-related aspects throughout the process life-cycle by integrating smart monitoring, intelligent early warning, intelligent decision-making, and optimization-based pollution reduction techniques. Green manufacturing can significantly improve the safety and efficiency of the process industries, and is likely to become a necessary requirement for high-level economic development.

2.2. Current status and major problems

The current status of the process safety and environmental protection capability of China's petrochemical industries can be described by accounting for the following three aspects (Fig. 3).

(1) **Mass production.** Statistical reports issued by the National Registration Center of Chemicals show that in 2017, more than 70 000 types of common chemicals were produced and consumed in the mainland of China, 3962 of which were hazardous chemicals. A hazardous chemical is a chemical that can potentially be harmful to the health of a human or animal, the environment, or property. Within decades of development, China has become one of the largest producers and consumers of chemicals. The State Administration of Work Safety reports that the number of hazardous chemical-related enterprises in China exceeds 300 000, with over 10 million employees. The length of the pipelines exceeds 120 000 km. The great economic value of these chemicals—especially hazardous chemicals—has not only resulted in the rapid development of the gross domestic product, but also led to increasingly serious situations related to environmental protection and public safety.

(2) **Non-uniform distribution of chemical industries.** In view of the population distribution and economic mismatch in the west-to-east direction of the mainland of China, the petroleum and chemical-related enterprises are mostly located in the eastern coastal areas (Fig. 4). However, for a specific chemical, the life-cycle processes of production, storage, transportation, usage, and waste usually occur in different plants, counties, cities, or even provinces. As a result, process safety and environmental protection should be considered on a larger spatial and temporal scale; however, this is not an easy task due to the complexities associated with the different stages, including material treatment and information flows. To solve these issues, more effort is needed in information integration and data analysis, which can be achieved using AI and cloud computing.

(3) **Higher safety and environmental requirements.** Economic development is improving the general living standard in China, making environmental deterioration less acceptable for residents who are pursuing a higher quality of life. Environment-related issues are attracting increasing attention from both government and society. A change of public consciousness is driving the government to drop the crude mode of economic development and pursue sustainable development instead. In addition, the 13th Five-Year Plan requires a 20% reduction in the number of major accidents in 2020 and a 20% reduction in the number of related deaths, thereby increasing the demand for smart process monitoring and risk management systems in the petrochemical industry.

The current statuses of process industries other than the petrochemical industry are quite similar to what has been discussed above. Major problems that preclude green manufacturing in the process industry are listed here.

(1) **Information isolation among multiple fields.** In the process industry, the stages of production, storage, transportation, usage, and waste are interrelated. However, each stage focuses on its specific fields and has its own information and database systems. In reality, the processes in the life-cycle are physically connected; however, they are usually isolated from the perspective of information processing. Inappropriate information exchange among different processes hinders the comprehensive analysis of process life-cycle data. For example, if information about materials and the real-time location of hazardous chemical transportation can be considered in the dynamic risk assessment process, the likelihood of potential accidents can be estimated and risk can be better managed, with dynamic routines and emergency preparedness.

Current status		
Mass production	Non-uniform distribution of chemical industries	Higher safety and environmental requirements
More than 70 000 common chemicals; 3 962 hazardous chemicals; More than 300 000 hazardous chemical enterprises; • 17 000 manufacturing enterprises • 265 000 management enterprises • 5 500 storage enterprises • 11 000 transportation enterprises 10 million employees; 120 000 km of pipelines	Production, storage, transportation, use, waste and other processes occur in different provinces, cities, districts, and counties. A list of provinces (the number of manufacturing enterprises exceeds 1 500) 1. Shandong 2. Jiangsu 3. Guangdong 4. Zhejiang ...	74 hazard chemicals under key regulation

Fig. 3. Three aspects of the current status of the process safety and environmental protection capability of China's petrochemical industries.

Distribution of chemical industries			
Province	Quantity	Province	Quantity
Xinjiang	276	Shandong	2718
Ningxia	236	Jiangsu	2644
Gansu	195	Zhejiang	1695
Qinghai	52	Guangdong	1608
Tibet	5	Henan	1003
...	...	...	...
Western inland areas		Eastern coastal areas	

Fig. 4. Distribution of chemical enterprises in the mainland of China.

The possibility of accidents can then be reduced to an acceptable level and major accidents can be avoided. Therefore, integrating abundant information and establishing knowledge bases are challenging tasks that should be addressed first in the implementation of green manufacturing in the process industry.

(2) **Diverse information types and different kinds of data.** From the life-cycle perspective, the different stages of, for example, manufacturing, storage, and road transportation have their own specialties and particular knowledge. These differences occur in both the spatial and temporal dimensions. For example, the values of the temperature, pressure, level, and so forth are important because of embedded information regarding abnormal situations and other quality-related issues. When it comes to transportation, the routes, enterprises, real-time locations, vehicle status, and drivers' statuses are key aspects in transport safety. However, this information belongs to different systems that are difficult to communicate or integrate, not to mention differences in the data sampling rate, data formats, and data collection methods. These issues pose difficulties to the integration of safety-related information into the process life-cycle. Moreover, there are various disciplines behind the data collected during different life-cycle processes, and the integration of both factual data and knowledge into a consistent system is another challenging task.

(3) **Lack of a process-safety-oriented decision-making system.** For large-scale production in the process industry—especially in the petrochemical industry—geometric magnification is the best way to reduce costs and gain the benefits of scale. A large-scale production then results in complex supply chains and marking systems. The industry spreads out of one city, one province, and finally forms a huge network across the nation. In industrial chains, the production and demand in different spatial and temporal regions requires national transportation and storage networks, covering densely populated areas and various natural environments. The bulk storage of hazardous chemicals could pose a major risk to local communities. When it comes to production, the scale-up of the process requires a fully functional control system, correct human operation, and high level of mechanical integrity. If not handled correctly in time, any small mistakes or failures might trigger a serious accident. In other words, in terms of risk, too many factors are correlated and their interactions are usually not intuitive. Risk management is taken into account during the design of modern petrochemical plants, by integrating multiple practical hazardous identification and management techniques such as hazard and operability analysis (HAZOP), layer of protection analysis (LOPA), and system integrity level (SIL). Yet these analyses are somewhat static and the relevant documentation is beyond the reach of onsite operators, who need to be fully aware of the situation and of the potential consequences of their actions. The behavior of operators is highly dependent on training and management. Accidents recently occurred at the German chemical company BASF [19,20], resulting in casualties and economic losses. The cause of the accidents was closely related to operation errors on the part of the staff. This case reflects the necessity of having a decision-making system, which is significant for operation safety. Thus, there is a demand for an intelligent system that can take advantage of the static knowledge embedded in existing documents such as HAZOP, LOPA, and SIL, in order to dynamically analyze the situation and provide safety-related suggestions. Such a system might improve safety management by taking more safety-related factors into consideration than a human worker in a time-demanding situation. Another key aspect of safety practice is inherently safer design—a concept that permanently reduces or eliminates the hazards associated with materials and operations used in the process—which is widely applied through the very early stages of process design, normal operation, and change, until the end-of-life of a facility. Chemical processes have structural similarities from a safety perspective. The application of an inherently safer design in one chemical process facility would set a precedent for other facilities. In order to support safety-oriented decision-making in a broader view, the basic rule and concept of inherently safer design must be extracted and integrated into intelligent systems, along with the experiences gained from several successful cases. Finally, the general challenge of establishing a decision-making system for process safety lies in how human experience and knowledge written in natural language can be understood and used by machines.

(4) **Lack of early warning and risk tracing systems.** In the process industry, most accidents become severe because of the lack of an effective warning mechanism [21]. In general, a petrochemical process runs in multiple configurations, each with its own operational window and/or restrictions. As the process is controlled by automation systems, small fluctuations in process parameters can spread to the downstream processes and affect critical units. The complex inner correlations of the process parameters usually make these changes and fluctuations in critical units non-apparent for operators to recognize. At present, process supervisors and operators rely on their experience to address this issue. Proper process functioning requires the ability to recognize abnormal situations based on sophisticated process-monitoring systems, in order to identify actual process configurations and trends. The diagnosis functions should work in real time to evaluate the current risk and potential shifts of normal operation configurations to abnormal cases. An assistant decision-making system is needed that can provide possible causes for the current situation and delineate potential consequences if no action is taken. Unfortunately, no such smart system is currently available.

3. Artificial intelligence for green manufacturing

AI [22], usually referred to as machine intelligence, has become an important branch of computer science and automation. AI combines domain knowledge from computer science, automation, information engineering, mathematics, psychology, linguistics, and philosophy. The problems faced by AI have been separated into several sub-problems based on specific characteristics or capabilities, as shown in Fig. 5.

The four major problems in green manufacturing can be divided into three categories, according to their characteristics: ① information integration, ② dynamic risk assessment and aid in decision-making, and ③ early warning. Several techniques are available to address these problems and achieve green manufacturing, including knowledge graphs, Bayesian networks, and deep learning, which will be detailed in the following.

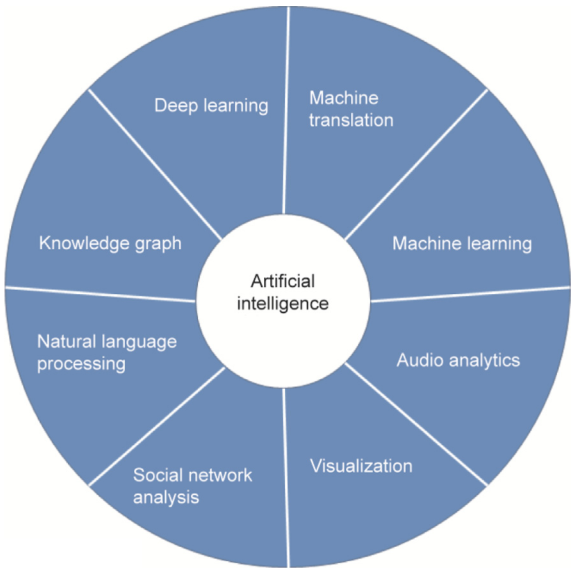

Fig. 5. Several sub-problems in artificial intelligence.

3.1. Information integration via knowledge graphs

A knowledge graph is a famous and promising technique for organizing linked data in the field of AI. It is a structured semantic network that describes concepts and their relationships. Moreover, knowledge graphs can provide reasoning and inference capabilities based on rules or deep learning strategies, and these capabilities empower the implication of relations between "entities" within predefined classes. Knowledge graphs are widely used in Internet-based applications such as encyclopedias, social networks, online financial systems, and social security systems [23,24].

Unlike the general knowledge used in Internet-related applications, the process industry requires much greater specialization in chemical engineering, process safety, process control, automation, and mechanical aspects. The implementation of knowledge graphs in such a specialized industry requires not only factual information, but also the specific knowledge for the field. Knowledge modeling is usually difficult, and a deep understanding of the specific field is essential. Given the general procedure to build a knowledge graph of an arbitrary domain (Fig. 6) [25], the establishment of knowledge graph for process safety can be roughly divided into three stages: gathering process-safety-related information, knowledge fusion, and knowledge processing, as shown below.

(1) **Process-safety information extraction.** The construction of a knowledge graph starts with gathering relevant information [26] about process safety, including chemicals, reactions, process-related documents, control systems, mechanical information, and risk-related information. The coverage of this information and data should be broad and diverse, covering not only structural data but also diagrams, tables, and texts written in natural language. Because the key purpose of knowledge graphs is to generate linked data, the main challenge is to identify individual "entities" and their relationships from different data sources. These processes are usually referred to as entity extraction, relationship extraction, and attribute extraction [27,28].

- Entity extraction: Entity extraction refers to the automatic identification of named entities from text datasets. It is the most basic part of information extraction. It relies on a well-defined ontology schema to extract specific risk-related factors in the process industry. The data source usually includes operation manuals and maintenance sheets, as well as piping and instrumentation diagrams (P&IDs) and process flow diagram (PFD).
- Relationship extraction: Given extracted entities, the second step is to determine the relationship between entities. The relationship usually takes the form of semantic information or other tables or diagrams. In the petrochemical industry, information about causal safety aspects is generally contained in the process-hazard-analysis documents (e.g., HAZOP, LOPA, and SIL verification documents). Determining these cause–effect relationship usually requires deep understandings of risk, or at least knowing the factors that produce hazard.
- Attribute extraction: Process-related entities, such as pressure relief valves, have various definitions in different aspects, including materials and designed relief pressure. These attributes should also be extracted, as they contain some quantified information that can be compared or modeled.

(2) **Process-safety knowledge fusion.** Through safety information extraction, a complete description of risk factors and their

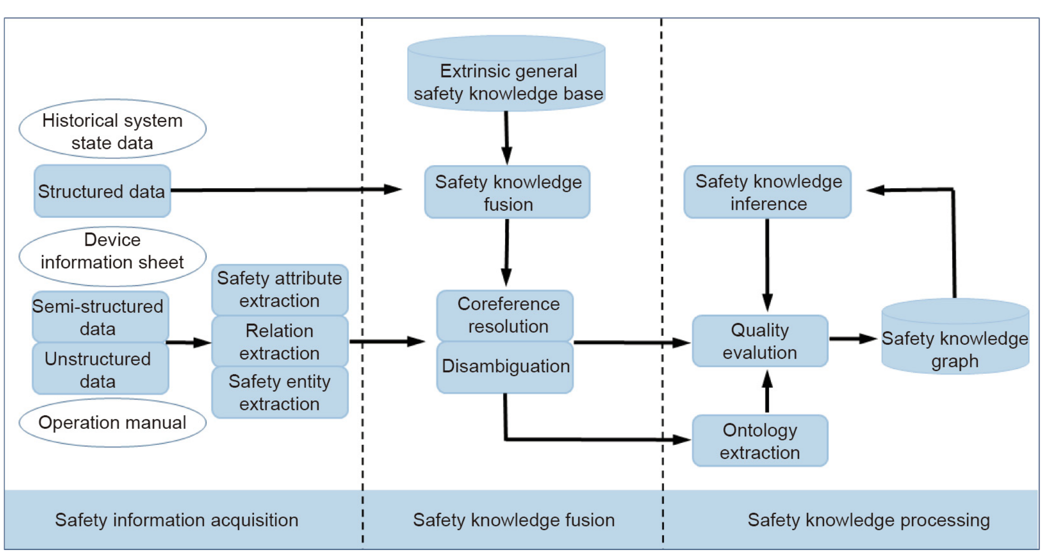

Fig. 6. Technical architecture of a typical knowledge graph [25].

relationships can be carried out. However, these results may contain many redundancies and errors. Moreover, the relationships between data are flat, lacking hierarchy and logic. Through knowledge fusion [29], the ambiguity of concepts can be recognized and eliminated either automatically or manually, eliminating redundancies and errors.

(3) **Process-safety knowledge processing.** After knowledge fusion, the ambiguity of the entity can be eliminated. Next, a series of basic factual expressions can be expressed. In process-safety practice, the analysis of safety-related factors is of great importance. Potential hazards and incident likelihoods should be identified and estimated. To achieve automatic identification of process hazards, process-safety-related knowledge should be applied to describe the details of each particular chemical process, including the process, equipment, operability, and mechanism. Deviations of certain process parameters should be identified as an initial event, and causal relationships linking trigger events to downstream processes should be diagnosed using predefined rules and embedded knowledge. Knowledge processing should provide such capabilities for automatic safety analysis. Knowledge processing mainly includes three aspects: safety ontology reconstruction, reasoning, and quality assessment.

- Safety ontology reconstruction: Ontology refers to a norm that models and describes concepts in the objective world. An ontology clearly defines the concepts of knowledge in certain domains and their connections in a formal manner. Process-safety ontology can be constructed initially by brainstorming via the existing knowledge. Once sufficient linked data are collected, the corresponding ontology can be reconstructed from the data common characteristics using machine learning methods.
- Reasoning of risk relationship: Reasoning refers to discovering the potential relationship between existing entities based on predefined rules or existing characteristics in data. Through knowledge reasoning, new process-safety knowledge can be discovered or estimated from existing entity networks. Existing hazard identification and analysis methods have already provided information about risk metrics and cause–effect relationships between various deviations. Theoretically, reasoning using the process-safety knowledge graph is supplemental to the identification of unrecognized risk-related factors that would improve operational safety or functional safety. Reasoning methods can be divided into two categories: logic-based reasoning [30] and graph-based reasoning [31].
- Quality assessment: This is also important for building a process-safety knowledge graph. With the state-of-art knowledge extraction techniques, the facts and knowledge obtained from data may still have errors and noises. The quality of safety-related knowledge cannot be guaranteed through automatic knowledge extraction and reasoning. Before merging the newly extracted data with the domain knowledge graph, a quality assessment is necessary in order to evaluate the precision, recall, and F_1-score (weighted average of precision and recall) criteria of the newly acquired data.

To summarize, knowledge graphs provide an effective method to integrate process-industry-related information. The existing problems of information gaps, data divergence, and the expression of complicated relationships implied in data can all be addressed using knowledge graphs.

3.2. Risk assessment and decision-making using Bayesian networks

Bayesian networks [32,33] are probabilistic graphical models that use directed acyclic graphs to capture probabilistic relationships between variables, and to capture the variables' conditional dependencies. In the process industry, risk factors can be associated with different types of abnormalities and anomalies using probabilistic relationships. For example, assuming there is a likelihood of a runaway reaction in a coking furnace, a reactor for delayed coking process, five primary process parameters should be analyzed considering the reaction hazard. These parameters are: ① and ② the temperature and flow rate of hot materials, ③ and ④ the temperature and flow rate of heated materials, and ⑤ the coking degree in the furnace tube. All these parameters have different probabilities of deviation. A Bayesian network is able to describe the complex probabilistic relationships between the above five factors and a runaway reaction. This method can also be applied to other potential accidents and associated risk factors. By considering accuracy, parameters in a Bayesian network should be tuned carefully to achieve good performance. Thus, parameters that are based on available prior knowledge can be optimized following the principle of maximal entropy, and estimation can be performed using the maximal likelihood approach. A Bayesian network can then accurately trace risk factors. As described above, by comprehensively analyzing data, a Bayesian network is able to find an abnormal source to estimate whether there will be a runaway reaction in a coking furnace. Furthermore, using the linked data provided by a knowledge graph for process safety, a Bayesian network can provide emergency solutions corresponding to different abnormalities.

3.3. Incident early warning based on deep learning

Deep learning [34], also known as deep structured learning, is a subclass of machine learning. It imitates the function of the human brain to interpret data using multi-layered neural networks. In the process industry, the possibility of a potential accident is usually implied in the fluctuation of process-monitoring data. For example, a composition change in a feed to an exothermic reaction might result in a more significant heat generation in the reactors, thereby narrowing the applicable operational window. As a consequence, fluctuations in the process parameters might exceed the safety limit and lead to runaway reactions, manifested by a rapid temperature increase. If the relationships between the temperature/pressure rise in the upstream unit and potential explosion consequences in the downstream unit are determined prior to the effects, a specific early warning function could be designed. Unfortunately, in reality, the number of process-monitoring parameters is too great, and the implied relationships between parameter changes and potential risks are too complicated for humans to grasp. In this situation, deep learning can be used to recognize the patterns of potential accidents and the associated parameter changes. In addition, if detailed information about labeled process-monitoring data, process equipment, and human operations is available, the probability of potential accidents can be estimated from measured data. Labeled big data [35] constitutes the basis for deep learning and related techniques in risk identification and evaluation. However, in practical situations, big data collected from processes usually feature missing data and outliers, and lack validated labels. Therefore, available data are typically far from adequate, and incident early warnings in current industrial applications rely mainly on expert experiences and alarm systems.

4. Technical challenges

Although knowledge graphs have been applied in several specialized industries, they are still a new technique for the manufacturing industry. Considering the complex safety relations in the process industry, the implementation of knowledge graphs in the process industry still faces several technical challenges, as described below.

(1) **Knowledge acquisition with scarce labels for process safety.** Knowledge acquisition in a sparse sampling environment is a common step in the establishment of a knowledge graph. When applied in the process industry, it may face some difficulties due to the complexity of chemical processes. A process-safety application is a life-cycle procedure that requires the process design, equipment, automation, and human action to be perfectly functional. If any of these malfunction, incidents may occur. Then, to build a knowledge graph that describes the process-safety-related information, abundant relevant data should be provided. However, for the life-cycle of chemical processes, these relevant data are usually in different domains, and acquiring such interdisciplinary data is difficult. Furthermore, for the process-safety analysis, the most valuable data are the real-time variation of process monitoring with labels on abnormal situations and failures. However, these labels are generally unavailable in applications of process-safety analysis.

(2) **Knowledge-based reasoning about process safety.** Due to the urgent need of risk reduction and safer operation in the process industry, process monitoring, abnormal condition tracing, and consequence assessment should be timely and reliable. Knowledge reasoning may uncover some cause-and-effect relationships that are not apparent to humans, thus providing supplementary information for the process-safety analysis. Nowadays, state-of-the-art reasoning methods in knowledge graphs achieve an accuracy of about 80% [36]; however, this level is insufficient for practical use in process-safety analysis. Current techniques related to knowledge reasoning should be improved or new techniques should be proposed to satisfy the safety requirements of the process industry.

(3) **Accurate fusion of heterogeneous data from multiple sources.** In the process industry, data related to process safety come in two forms: the static form and dynamic form. Static data comprise process information and related hazard analysis documents that are not changing frequently, while dynamic data mainly describe the process state that changes all the time. However, in practice, the data obtained usually contain ambiguities that will increase the difficulty of knowledge acquisition. There are two possible solutions. The first focuses on data preprocessing, while the second emphasizes domain-based knowledge acquisition and performs knowledge fusion on acquired data.

(4) **Effective learning strategies for dynamic risk assessment and aided decision-making.** Knowledge graphs provide an efficient means of integrating static knowledge and facts related to petrochemical process safety. Ideally, cause-and-effect relationships in a chemical process are retained in the relationship between different entities and corresponding rules or axioms. Although knowledge graphs enable cause-and-effect analysis from specific deviations, the appropriate deviation itself is usually difficult to identify. Real-time data from the process-monitoring system is necessary to identify possible deviations from the normal state. With a knowledge graph, appropriate machine learning methods are needed for abnormal situation classification. Then, with a reasoning engine, dynamic propagation of certain deviations from the initial state can be evaluated, and several event chains can be identified for different consequences. Finally, with dynamic risk assessment performed on each event chain, a final decision can be made. To achieve this end, abundant information is required on process reliability, equipment failure modes and corresponding effects, operational procedures, and other fields. Unfortunately, in practice, high-quality data are far from sufficient to ensure algorithmic learning. The challenge lies in dealing with small sample sizes of data.

5. Current and future works

To realize green manufacturing via AI, we have already started studies on process-safety knowledge integration for the delayed coking process. The current result is shown in Fig. 7. As shown in

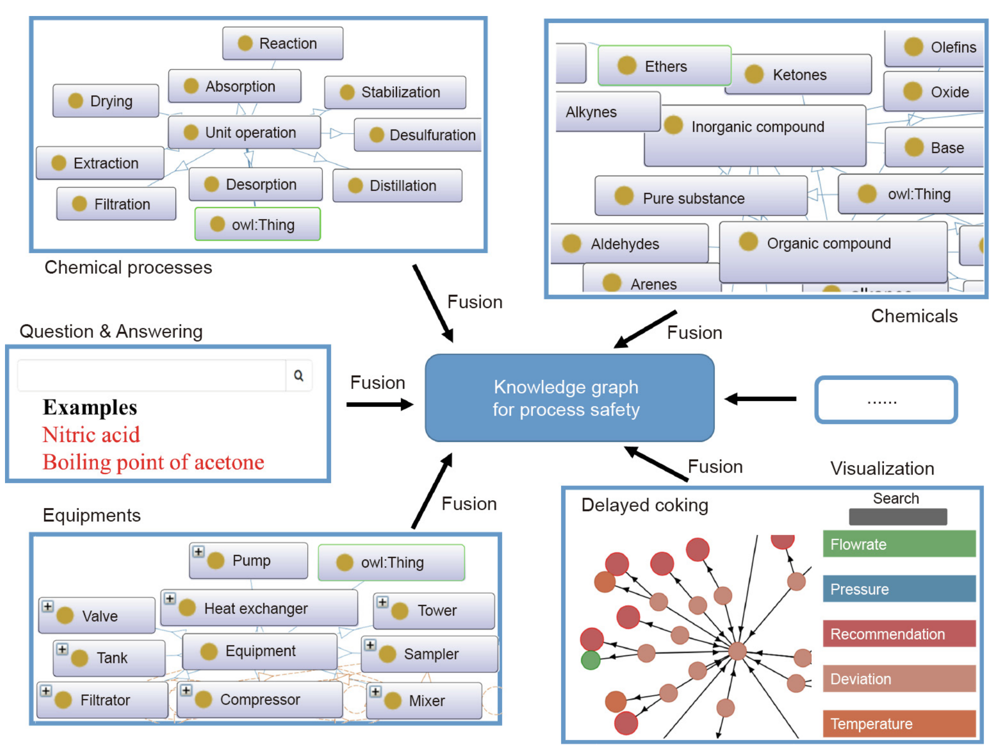

Fig. 7. Framework of current and future works.

the figure, an integrated ontology was proposed, covering the equipment, chemical process, and chemical substance in the delayed coking process. In the knowledge graph, every single element related to process safety is considered, including the upper and lower bounds on process parameters, the upstream and downstream relationships, and the composition of the deviation of process parameters. We also concentrated on visualization, question answering, and achieved corresponding results, also depicted in Fig. 7. The purpose of realizing visualization and question answering is to enhance the capacity of human–machine interaction, which is a significant part of the realization of smart manufacturing.

In the future, we will focus on the cause-and-effect relationships between arbitrary deviations and their influence on the downstream process parameters. The initial deviation propagates downstream to form an event tree, which is subsequently analyzed to support decision-making. The goal is to identify abnormal situations by using proper process-monitoring techniques, and to enable rapid logical analysis by following the ordinary fault tree and event tree in an automatic manner. Moreover, with an increase in the depth and breadth of the data integrated in the knowledge graph, realization of incident early warnings, risk tracing, and aided decision-making will be achieved in our future work via deep learning and Bayesian networks.

6. Conclusions

This paper has discussed in detail the importance, current status, and major problems faced by green manufacturing in the process industry. We have reviewed several attractive technologies in the field of AI, including knowledge graphs, Bayesian networks, and deep learning. These techniques provide methods for solving major problems in green manufacturing. Based on sufficient analysis and discussion, specific technical challenges for process safety were discussed. These challenges include knowledge acquisition and reasoning about scarce error data, accurate fusion of heterogeneous data, and early warning and aided decision-making. Possible ways of addressing these challenges were proposed and related achievements were discussed.

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Compliance with ethics guidelines

Shuai Mao, Bing Wang, Yang Tang, and Feng Qian declare that they have no conflict of interest or financial conflicts to disclose.

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