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Research
Smart Process Manufacturing—Perspective

Smart Manufacturing for the Oil Refining and Petrochemical Industry

Zhihong Yuan [a], Weizhong Qin [b], Jinsong Zhao [a,*]

[a] *Department of Chemical Engineering, Tsinghua University, Beijing 100084, China*
[b] *China Petroleum and Chemical Corporation Jiujiang Company, Jiujiang 332004, China*

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ABSTRACT

Smart manufacturing will transform the oil refining and petrochemical sector into a connected, information-driven environment. Using real-time and high-value support systems, smart manufacturing enables a coordinated and performance-oriented manufacturing enterprise that responds quickly to customer demands and minimizes energy and material usage, while radically improving sustainability, productivity, innovation, and economic competitiveness. In this paper, several examples of the application of so-called "smart manufacturing" for the petrochemical sector are demonstrated, such as the fault detection of a catalytic cracking unit driven by big data, advanced optimization for the planning and scheduling of oil refinery sites, and more. Key scientific factors and challenges for the further smart manufacturing of chemical and petrochemical processes are identified.

1. Introduction

Advanced or smart manufacturing has recently been gaining increasing attention from the academia and industry in major economies. For example, Germany's Industry 4.0, which integrates resources, information, materials, and people to formulate a cyber-physical system, has been the priority of many enterprises, especially those that are small and medium-sized. In the United States, the Smart Manufacturing Leadership Coalition (SMLC), which has its headquarters in Los Angeles, California, leads the new Smart Manufacturing Innovation Institute, in partnership with the US Department of Energy [1]. Aiming to spur advances in smart sensors and digital process controls, which can radically enhance the efficiency of advanced manufacturing in the United States, the SMLC brings together a public-private consortium of nearly 200 partners from the academic, industrial, and non-profit arenas, and brings in over 140 million USD from these members. Unlike the United States and Germany, which have developed industries, China is in its developing stage. Many of the control/management systems and engineers in China are still stuck at the level of Industry 2.0. Therefore, in order to address China's national conditions and the gap between national and developed economics, the Chinese government launched a strategy called Made in China 2025 in 2015 [2]. Smart manufacturing is regarded as the central element in the Made in China 2025 strategy. Both Industry 4.0 and smart manufacturing focus on transforming the industrial sector into a connected, information-driven environment, in which production systems and supply networks can be optimized via real-time and customer-oriented internal vertical integration within smart factories, horizontal integration within upstream and downstream enterprises, and end-to-end integration from the supply chain to the customers.

Process systems engineering (PSE), which has played an essential role in facilitating advanced chemical processing and production since the 1960s [3], will play a key role in achieving smart manufacturing in oil refineries and petrochemical plants by encompassing the following advances in the processing unit, the plant, the enterprise, and the supply chain:

- Advanced sensing and instrumentation;
- Real-time flowsheet optimization and control under uncertainty;
- Green molecular design for high-value-added products;
- Adjustable big data analytics for process optimization, monitoring, and management;
- Advanced hardware and software platforms; and
- Predictive modeling and simulation technologies.

It should be noted that Fig. 1 merely highlights the key features of smart manufacturing from the perspectives of PSE, rather than

* Corresponding author.
E-mail address: jinsongzhao@mail.tsinghua.edu.cn

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providing the framework of smart manufacturing. To our knowledge, smart manufacturing should combine information, technology (beyond PSE technologies), and human ingenuity in order to bring about a rapid revolution in the development and application of manufacturing intelligence, and to improve agility, flexibility, productivity, and quality. This paper briefly outlines examples of the application of so-called "smart manufacturing" at the China Petroleum and Chemical Corporation (Sinopec).

2. Brief overview of smart manufacturing at Sinopec

In China, Sinopec is a pioneer in the launching of smart process manufacturing. With the goal of smart manufacturing, Sinopec has established four demonstration projects since 2012: smart petrochemical pilot units (including Jiujiang, Zhenhai, Maoming, and Yanshan), an integrated business-management platform, an information technology shared-service center, and a mobile application [4]. Through almost four years of construction, great changes have taken place in the selected four smart pilots in terms of automation, digitalization, and visualization. For example, advanced control is now available for over 90% of all processes in these four pilots and productivity has improved by more than 10%. Production optimization has been shifted from off-line optimization to on-line integrated optimization.

Fig. 2 illustrates a general integrated optimization platform currently running at Sinopec Jiujiang Company. Based on existing commercial software such as a manufacturing excution system (MES), enterprise resource planning (ERP), and a laboratory information management system (LIMS), flowsheet optimization, planning, and scheduling are integrated. At Maoming and Yanshan, integrated real-time optimization and advanced process control have achieved profit-oriented closed-loop optimal running for ethylene production. Due to obvious improvements in the yields of ethylene and propylene, the overall incomes for Yanshan and Maoming have improved by 25.12 million and 41.94 million CNY per year, respectively. In addition to the implementation of an integrated optimization framework and platform, big data analytic technologies and tools have been studied and implemented for abnormal event management. For example, big data (i.e., data size of around 50 TB) analytics have been utilized for production analysis and early warning for fluidized catalytic cracking units and reformers. Not only can big data analytics find new root causes, but they can also predict an alarm in advance.

Some experts claim that Sinopec has formulated a so-called "version 1.0 of smart manufacturing." However, as described above, the activities at Sinopec simply collect and integrate existing commercial optimization and simulation software, and include few new scientific methods or tools. In addition, no evaluation criteria exist that can be used to assess what smart manufacturing actually is. In other words, once true smart manufacturing has been implemented, it will fundamentally change the ways in which products are invented, manufactured, shipped, and sold. To some extent, there is still a very

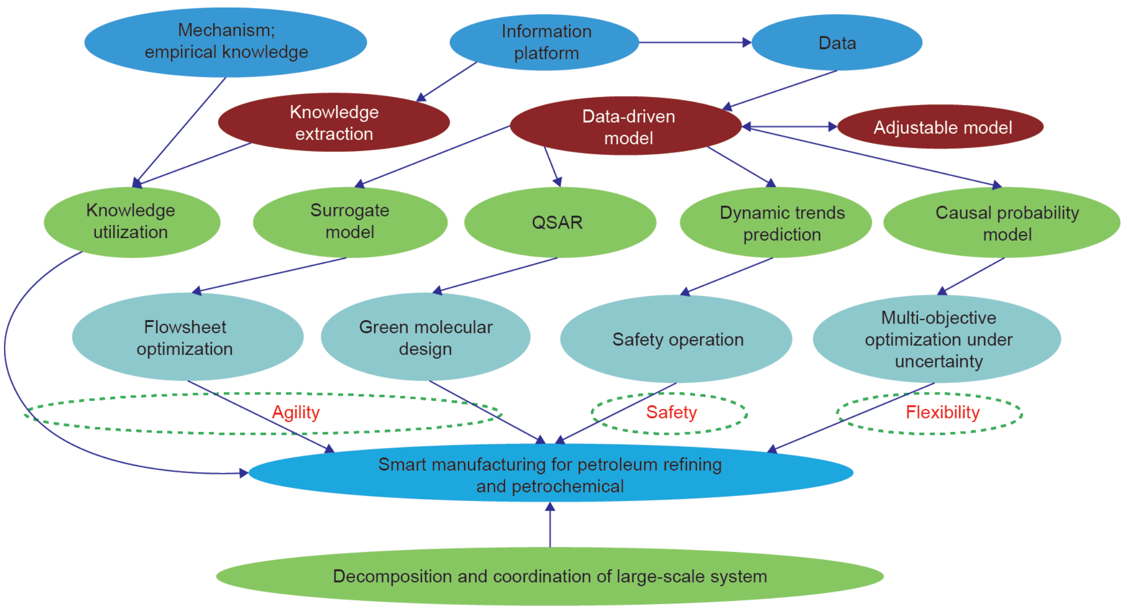

Fig. 1. Key features of smart manufacturing for the oil refining and petrochemical industries. QSAR: quantitative structure-activity relationship.

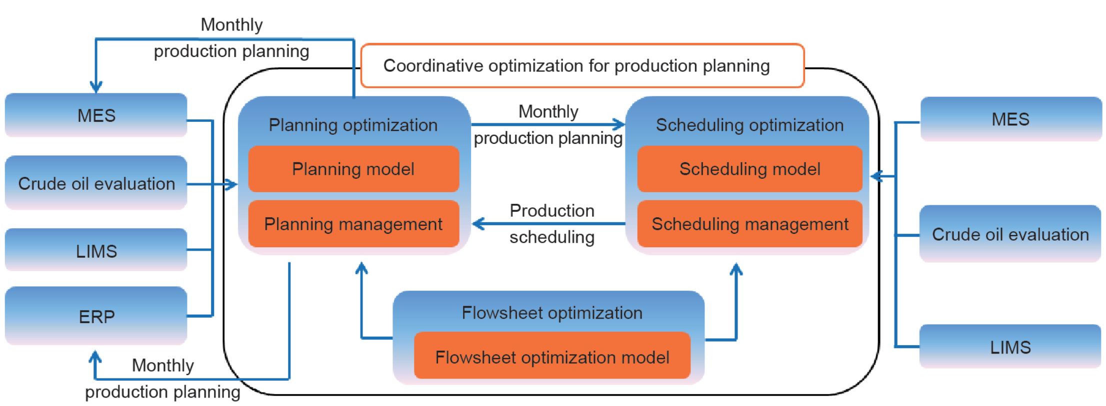

Fig. 2. The integrated optimization platform at Sinopec Jiujiang Company.

long way to go to achieve genuine smart process manufacturing, given that its six representative topics include integration, automation, networking, modeling, digitalization, and visualization. We must be seriously aware of the opportunities, difficulties, and challenges that lie ahead.

3. Opportunities and challenges

3.1. Operational agility

One of the key attributes of smart process manufacturing is operational agility—that is, a fast response to new situations caused by variations in feedstock, market demand, and price. Clearly, such perturbations will significantly affect plant performance. Thus, switches in operational strategies (i.e., process flowsheet reconstruction and temperature/flowrate/pressure transitions) are extremely necessary. Here, the first challenge is how the correct set points can be quickly obtained for the lowest-level control systems. From an industrial perspective, experts' heuristic knowledge and operational knowledge are the best choice, although existing knowledge is unlikely to be able to cover all possible operation cases. The second challenge is the accuracy of the knowledge-driven approach. Recently, Zhang and Chen proposed a fuzzy matching strategy to enhance the operational agility of an industrial catalytic cracking unit (unpublished data). From an academic perspective, model-based real-time optimization is the main approach [5]. Here, the first question is where we can obtain reliable first-principle models for chemical processing units, especially for complex reactors; the second question is how we can efficiently solve the real-time optimization model; and the third question is whether the industry will trust and adopt the optimization results.

3.2. Adjustable data-driven model building

In the previous subsection, we mentioned the barriers to solving an optimization model that is subject to a complex first-principle model. One possible solution is to use a data-driven surrogate model to replace the original first-principle model. Neural network, kriging, principle component analysis, supported vector machine, mathematical programming, and other statistical methods have been widely employed to generate surrogate models for fault detection, process control, and optimization [6,7]. When generating a surrogate model, we must identify where the surrogate model will be used and implemented—that is, whether it will be used for trends prediction or for flowsheet optimization. If the surrogate model is to be used for flowsheet optimization, a neural network-driven surrogate model may lead to considerable computational barriers and will not be able to obtain high-accuracy solutions. No matter which method is utilized to generate the surrogate model, external ductility is of paramount importance. Here, the first question is how many datasets are sufficient to build a surrogate model with high accuracy; and the second question is how an adjustable date-driven model can be generated. Accuracy should be validated by industrial datasets. When datasets are obtained from real industrial plants, data reconciliation and gross error detection [8] should be employed.

3.3. Abnormal situation management

It is notable that the focus of smart manufacturing should not only be on the maximization of economic competitiveness, but also on the reduction of safety incidents. Therefore, safety risk intelligence should be an essential feature in smart process manufacturing [9]. In other words, risk assessment should be the first critical step in abnormal situation management (ASM) in order to obtain a preliminary profile of the risk scenarios to be managed. In the context of big data, alarm management, process monitoring, equipment fault diagnosis, and human behavior monitoring should be effectively integrated in order to achieve a reliable and scalable ASM platform. For example, Fig. 3 demonstrates a framework of fault detection

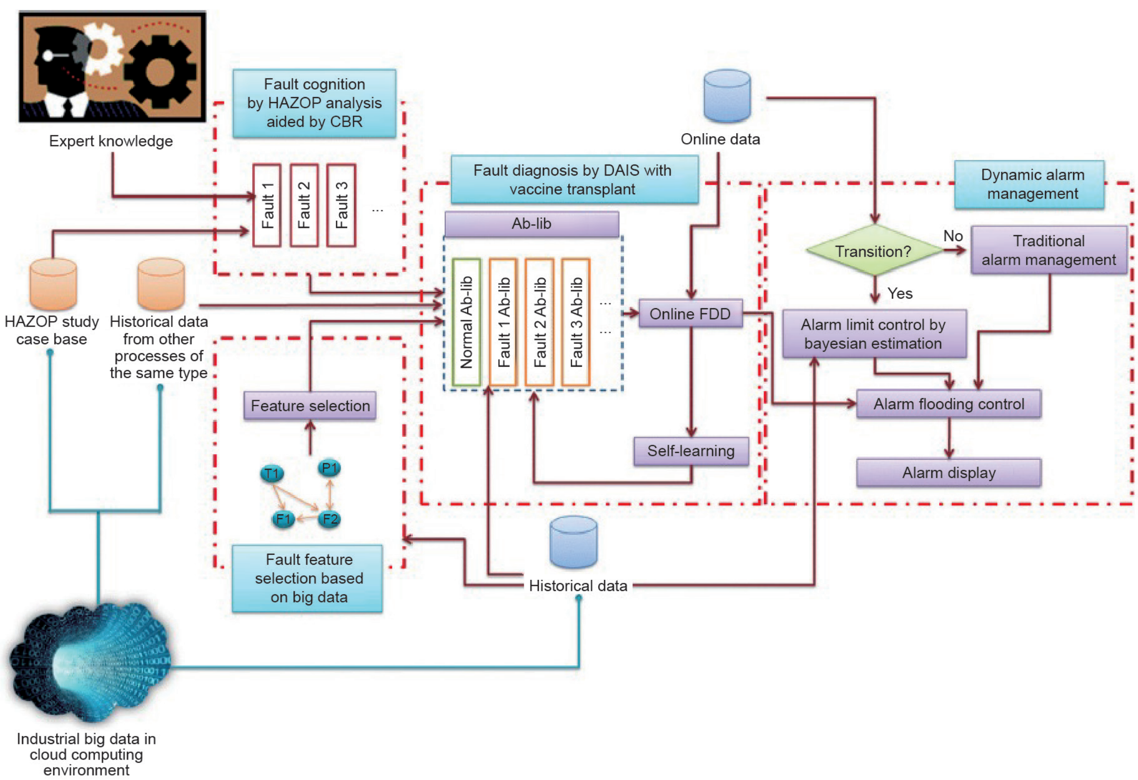

Fig. 3. Framework of fault detection and diagnosis with big data in a cloud-computing environment. HAZOP: hazard and operation; CBR: case-based reasoning; DAIS: dynamic artificial immune system; Ab-lib: antibody library; FDD: fault detection and diagnosis.

and diagnosis with big data in a cloud-computing environment that tackles the following challenges [10]:

- How can the faults to be diagnosed in any given chemical process be identified?
- How can all of the faults in a chemical process that require diagnosis be defined?
- How many features does each fault possess?
- Can a fault be diagnosed in a new chemical process if fault data samples do not exist?

Regarding the big data, how large and/or diverse should the dataset be that is available for use? Even if a clear answer to this question is found, how can the big data be effectively compressed and stored? Thus, when using big data for smart process manufacturing, knowledge of both computer science and chemical engineering are extremely necessary.

3.4. Planning and scheduling for an entire oil refinery or petrochemical plant

Optimal planning and scheduling of various operations in an oil refinery or petrochemical plant via mathematical modeling and global optimization provide considerable opportunities for saving costs, increasing profit margins, and improving energy efficiency and demand satisfaction. To the best of our knowledge, the capacity to complete the planning and scheduling of an entire oil refinery or petrochemical plant—a key feature of smart manufacturing—has been limited until now [11]. The full set of operations generally contains three components: crude oil blending and processing, processing unit operations, and product blending and distribution [12]. The consequent question is how to formulate a reliable mixed-integer (non) linear programming (MI(N)LP) model. It is difficult to imagine the scale of an optimization model for the planning and scheduling of an entire oil refinery or petrochemical plant. If the complex equations that represent certain reaction units are directly inserted into the MI(N)LP model, it is known that the optimization model will be intractable. The first challenge is how to set up simple but suitable models to represent the operation conditions, feedstock properties, and yields of main products; and the second challenge is how to solve the resulting very large-scale MINLP model. To address the first challenge, an adjustable data-driven model can be considered if reliable input-output datasets for the real operation can be obtained. To address the second challenge, decomposition coordination appears to be the preliminary tool, although agent-based algorithms should also be tested.

4. Conclusions

This paper outlined the main opportunities and challenges regarding smart manufacturing for an oil refinery or petrochemical plant by demonstrating the progress in so-called "smart manufacturing" at Sinopec. Although considerable progress has been made, there is still a long way to go to achieve true smart process manufacturing. PSE is expected to take a central role in guiding, and perhaps shortening, the new journey toward smart process manufacturing. From an academic perspective, it is best for the industry to provide the test beds; while from an industrial perspective, it is best for academia to offer a reliable and scalable platform that includes hardware and software to update the instrument technology level. In fact, these two aspects complement each other. An industry-university research coalition is urgently needed for the future.

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Compliance with ethics guidelines

Zhihong Yuan and Jinsong Zhao declare that they have no conflict of interest or financial conflicts to disclose.

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