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REVIEW ARTICLE

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Development and challenges of planning and scheduling for petroleum and petrochemical production

Abstract Production planning and scheduling are becoming the core of production management, which support the decision of a petrochemical company. The optimization of production planning and scheduling is attempted by every refinery because it gains additional profit and stabilizes the daily production. The optimization problem considered in industry and academic research is of different levels of realism and complexity, thus increasing the gap. Operation research with mathematical programming is a conventional approach used to address the planning and scheduling problem. Additionally, modeling the processes, objectives, and constraints and developing the optimization algorithms are significant for industry and research. This paper introduces the perspective of production planning and scheduling from the development viewpoint.

Keywords planning and scheduling, optimization, modeling

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1 Introduction

1.1 Perspectives on production planning and scheduling

Production planning and scheduling are essential business optimization strategies of the refinery and petrochemical industry. The production process in the petroleum and petrochemical industry is continuous and of large capacity. Therefore, the optimal decision is necessary for stable production and maximum profit of a company. Production planning generally determines the material purchase, unit load, and product distribution for a specific time (week, month, or year) according to the market demand. Meanwhile, production scheduling determines the process sequence and operation condition according to the material balance and real-time properties. Although planning and scheduling are of different time scales, the common considerations contribute to the close relationship between the two activities. The leading companies, such as SINOPEC, BP, Exxon Mobil, and Shell, are taking considerable effort to optimize their planning and scheduling to cope with the changes in the market and environmental policies.

Time and space are two rules that must be observed in planning and scheduling. For instance, long-term planning and short-term scheduling, continuous- and discrete-time planning (scheduling) belong to the scale of time. The purchasing, producing, selling plan, or the upstream, midstream, and downstream planning (scheduling) are under the scale of space. Reaching the overall maximum profit considering the two scales in plant-wide optimization is challenging. Although planning and scheduling are different business optimization strategies, both aim to determine the operation for a specific time. Scheduling considers material balance and safety, usually in a short time with continuous operation. By contrast, planning focuses on material price and quality in extended periods with the discrete operation. Despite these differences, planning and scheduling problems will eventually be formulated into some linear programming (LP), nonlinear programming (NLP), mixed-integer linear programming (MILP), or mixed-integer nonlinear programming (MINLP) problems, which can be solved by the conventional optimization methods. Thus, an optimization problem is the general view of the planning and scheduling to minimize the cost and maximize the profit.

1.2 Development of software for production planning and scheduling

Planning and scheduling generally comprise two subsystems, namely, modeling and optimization, which have been considerably developed in the past five decades. The commercial software for planning and scheduling is based on mature technologies and has been widely applied in factories. Among these software developments, the Refinery and Petrochemical Modeling System (RPMS) by Honeywell Process Solutions is widely regarded as the earliest software for planning systems. This software employs a delta-base linear formulation providing a multi-plant, multi-period model using automatic recursion successive linear programming (SLP). The mixed-integer programming (MIP) and distributive recursion handling nonlinearities are also the built-in tools in RPMS. The system components include the databases of the refining and chemical processes for the practical application with RPMS, while the user interface components comprise a graphical user interface (GUI) and management system of data, modes, cases, and reports. The features of RPMS, which are also included in the Aspen Process Industry Modeling System (PIMS) by Aspen Technology and the Generalized Refining Transportation Marketing Planning System by Haverly Systems, are typical in planning software. Moreover, the PIMS-Advanced Optimization is designed for global optimization with a proprietary MINLP solver called Aspen XSLP. Another advanced feature in the type of software is the importation or integration of crude oil assays management systems, such as ASSAY2 by Honeywell Process Solutions, Aspen Assay Management by Aspen Technology, and H/CAMS by Haverly Systems. The commercial software facilitate the conversion from solving linear to solving nonlinear (mixed-integer) models, especially for a large-scale problem. The efficiency and convergence of solving the optimization problem are the main focuses of such software. Therefore, the convenience of users and the stability of the systems are considered.

As for the scheduling software, the Aspen Petroleum Scheduler™ is a widely used tool in refineries. This software can automatically schedule activities of crude oil distillation units (CDUs) and other downstream installations and configure the plan to match the actual operational constraints. The gap between planning and scheduling is reduced by sharing assay information with the PIMS. Engineers can obtain a comprehensive view of the results from its friendly user interface. However, the function of the crude oil schedule is limited in the software. Thus, users must manually decide the unloading plan of oil carriers, the oil blending recipe, and the flow rates in advance. The working process of the software is still semi-manual. Aspen Technology also developed the Aspen Plant Scheduler Family for other petrochemical scenarios. This scheduler comprises a three-tiered scheduling solution (Plant Scheduler, Plant Scheduler-EA, Plant Scheduler-EO) designed to address the varying degrees of scheduling complexity. Besides, H/Sched by Haverly Systems is an interactive scheduling system for refinery operation, crude oil, and product blending. These scheduling applications have implemented mixed-integer/linear programming optimization and advanced heuristics solvers. This type of software has been widely utilized by refinery and petrochemical companies. However, the software is often designed for some typical scenarios. Additional details must be considered because the schedule is involved with the execution level. Moreover, special rules, conditions, or demands are usually found in some specific enterprise, posing a challenge to the flexibility and expandability of software. Meanwhile, the software must be updated to handle the extensive uncertainty in the field, such as that in shipment, material property, and unit capacity. Thus, additional theoretical research in this area is necessary.

Except for these complete solution systems, algebraic modeling language (AML) such as General Algebraic Modeling System (GAMS) by GAMS Development Corporation, A Mathematical Programming Language (AMPL) by AMPL Optimization, and Linear, Interactive, and Discrete Optimizer (LINDO) by LINDO Systems, can also be used to perform planning and scheduling. The AML-based software allows users to develop the mathematical model for planning and scheduling optimization, which is also fit for some other optimization problems. Advanced Interactive Multidimensional Modeling System (AIMMS) by Paragon Decision Technology, and Industrial Modeling and Programming Language (IMPL) (Menezes et al., 2015) by Industrial Algorithms are those with higher-level modeling language for dedicated industrial application. The models of the planning and scheduling problem formulated in LP, MILP, and MINLP can be solved by a variety of commercial solvers, such as CPLEX by IBM, Gurobi, CONOPT (Drud, 1994), ANTIGONE (Misener and Floudas, 2014), and BARON (Sahinidis, 1996).

Whether the software is a completed solution or AML-based system, the general method used to handle planning and scheduling problems is the mathematical programming optimization to find the local or global optimum solution. The scale and the complexity of the problem impact the computational time and convergence of the optimization. Therefore, an appropriately simplified model is considered to be a tradeoff between the theoretical and practical models in the real application.

1.3 From industry to academic research

The industry needs the basic representation of the planning and scheduling problem considering usability and maintainability. By contrast, academic research considering the frontier and the innovation concentrate on the sophisticated problem. In the past decades, the industry and academic research have shown remarkable interest in production planning and scheduling from the fundamental modeling to the optimization algorithms. The industry seeks accurate representation, leading to the development of advanced techniques in academic research. The rest of this paper discusses academic research in different aspects. Section 2 shows the fundamental models of planning and scheduling problems and the optimization methods, which are general models and algorithms for the majority. The general models cannot express the complex correlations in the process for certain situations. Therefore, Section 3 discusses the process models, especially those with nonlinear correlations, used in the optimization problem. Section 4 illustrates the optimization under uncertainty, which is distinguished from the deterministic optimization due to the planning and scheduling considering uncertain prices and markets. Section 5 presents some industrial cases in the application of the virtual manufacturing system, which benefits from the optimization of planning and scheduling. Section 6 discusses some of the remaining challenges of planning and scheduling optimization. Section 7 proposes the conclusions.

2 Production planning and scheduling optimization

The production planning and scheduling activities cover the entire supply chain in a refinery, as shown in Fig. 1. A typical refinery supply chain comprises crude vessel transportation, crude storage and blending, distillation and fraction processes, and product distribution. The vessels carry the crude oil bought from the market, which is then sent to the crude oil storage tanks for blending and distillation. The crude oil is transported through pipelines and then separated into different distillation cuts as the intermediated resources for process units in the CDUs. The fractions are treated in the following reaction processes: Continuous catalyst reforming (CCR), fluid catalytic cracking (FCC), Davison circulating riser (DCR), hydrocracking (HCR), residuum desulfurization (RDS), solvent deasphalting (SDA), diesel hydrotreating (DHT), and residuum hydrotreating (RHT). The treatment aims to produce intermediate products, which are blended into several grades of naphtha, kerosene, gasoline, and diesel. Meanwhile, byproducts, such as liquefied petroleum gas, asphalt, coke, and some petrochemical products, are generated from the distillations and reactors. All the qualified products are stored in individual tanks and distributed to the sellers. The production planning and scheduling cover the refinery supply chain at different levels. The planner considers the activity chain, including the crude purchase, cut scheme, feed distribution, and production for a long time (month, season, or year), which is the upper level and extended for the recourses and the capacities. After the production plan is made, the scheduler must execute the plan by considering the detailed process information, such as the arrival of crude vessels, the real-time tank liquid level, unit condition, and repairment, to extend the monthly plan to weekly or daily and make this plan feasible. The optimization of planning and scheduling and their combination have attracted considerable attention in the research institute and industry through the development of mathematical models, advanced algorithms, and different constraints.

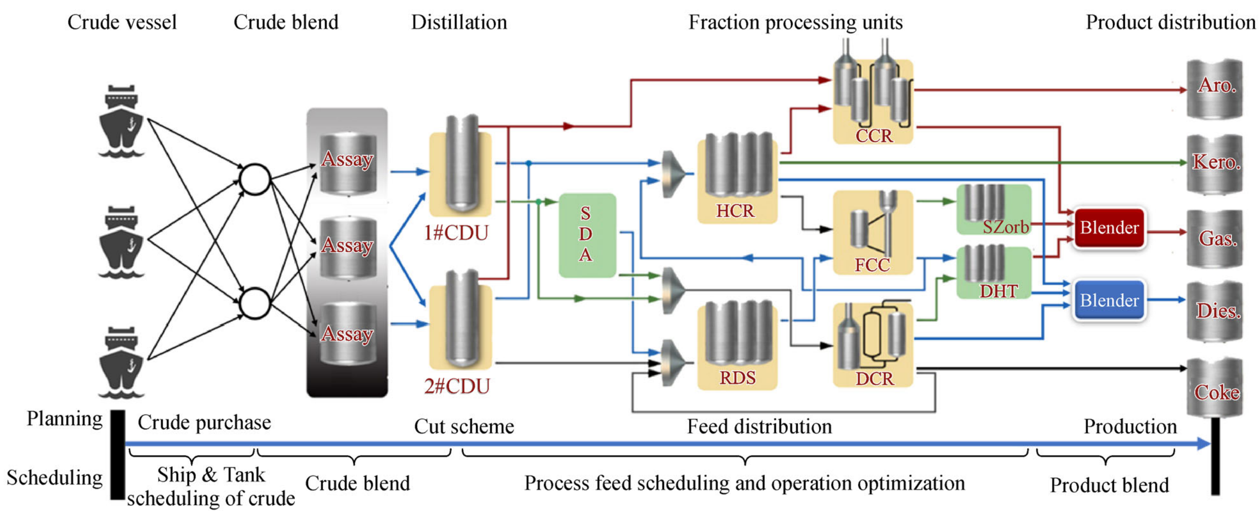

Fig. 1 Scope of planning and scheduling in a refinery supply chain.

2.1 Production planning and scheduling models

Optimization is the acknowledged approach to solve the planning and scheduling problem. A standard optimization problem comprises objective functions and constraints. In production planning and scheduling, the objective function can be profit-maximizing or cost-minimizing, while the constraints can be the equality or inequality depending on the mathematical representation of the problem. The MINLP-based planning model, which was proposed by Pinto et al. (2000), represents a general refinery topology with nonlinear process models and blending relations. The process unit models are considered to be nonlinear equations comprising blending relations and process equations. The bound constraints of the unit variables comprise product specifications, maximum and minimum unit feed flowrates, and limits on operating variables (Moro et al., 1998). The process unit model was adopted in an optimization problem of the petroleum supply chain with tank and pipeline models (Neiro and Pinto, 2004). Neiro and Pinto (2005) further extended the planning unit model to a complete and flexible formulation in a multiperiod planning problem.

The scheduling model is formulated as an MILP model for continuous- and discrete-time representations. The scheduling model is more specific than general planning models, such as short-term crude oil, multiproduct pipeline, and product blending scheduling. For short-term crude oil scheduling, a discrete-time model (Lee et al., 1996; Joly et al., 2002) and a continuous-time model (Jia et al., 2003; Jia and Ierapetritou, 2004; Mouret et al., 2009) determine the operation of crude oil unloading, transfer, and charging. For multiproduct pipeline scheduling, discrete-time and linear disjunction scheduling (Rejowski Jr and Pinto, 2003; 2004) and continuous-time (Rejowski Jr and Pinto, 2008) models respectively determine the loading and unloading operations of tanks and pipelines. For product blending scheduling, a gasoline blending and distribution model (Jia and Ierapetritou, 2003; Méndez et al., 2006) and a short-term multi-blending model (Glismann and Gruhn, 2001) determine the blending recipes and production volumes, respectively. Shah and Ierapetritou (2011) built a continuous-time scheduling model of production units and product blending considering quantity, quality, and logistics decisions. The above planning and scheduling models are built via mathematical programming, which focuses on the representation of the objective functions and constraints simplified from the real problem.

2.2 Optimization methods for the mathematical programming problem

2.2.1 Convex optimization and nonconvex local optimization

The mathematical programming method was adopted in the planning and scheduling optimization strategies around the late 20th century. Depending on the convex or nonconvex problem, the computational complexity can be P (polynomial) or NP (non-deterministic polynomial)-hard, contributing to the differences in optimization algorithms. The efficient algorithms of convex optimization and nonconvex local optimization used to solve large-scale LP, MILP, and NLP optimizations, such as CPLEX (early OSL by IBM) and CONOPT (Drud, 1994), are mature. The DICOPT (Grossmann and Raman, 2020) can solve a series of NLP and MILP sub-problems for the MINLP optimizations to obtain a local optimum solution. In the 1990s, the limits of computing power and the convergence of a mixed-integer or an NLP problem restricted the development of complex planning and scheduling models and global optimization strategies. Therefore, the large-scale problems were decomposed into sub-problems or assumed to be linear rather than nonlinear.

2.2.2 Global optimization algorithms

The formulation of a planning and scheduling problem involves integer variables and nonconvex nonlinear terms, such as the MILP and MINLP, which needs global optimization algorithms to find the global optimum. Some commercial solvers of global optimization, such as ANTIGONE (Misener and Floudas, 2014) and BARON (Sahinidis, 1996), are designed for the general mathematical programming problems. These algorithms are deterministic global optimization algorithms that can provide theoretical guarantees of a global optimum within a predefined tolerance in a finite time. Except for these global solvers, some researchers introduced dedicated global optimization algorithms, especially for the planning and scheduling problem. Karuppiah et al. (2008) presented an outer-approximation algorithm to obtain the global optimum of the scheduling model of crude oil movement, which only contained binary integer variables in the MINLP. Castillo et al. (2017a; 2017b) proposed a global optimization algorithm using piecewise McCormick relaxation and normalized multiparametric disaggregation technique for the scheduling of gasoline blending and large-scale refinery planning with bilinear terms. The global optimization based on heuristic strategies, such as using genetic algorithms in refinery scheduling optimization (Simao et al., 2007) and scheduling of crude oil operations (Hou et al., 2017), has also been applied to the production planning and scheduling problems.

The global optimization algorithms may be time-consuming when dealing with a large-scale problem (more than 5000 variables and constraints), especially with large numbers (over 500) of integer variables and nonlinear nonconvex terms (You et al., 2011; Castillo et al., 2017b). The decomposition strategy is adopted to accelerate the convergence of global optimization, which decomposes the large-scale problem into a series of small sub-problems. Shah et al. (2009) proposed a structural decomposition approach separating the problem as the intermediate storage tanks to provide a few constraints in the sub-problems. Shah et al. (2015) also decomposed the large-scale refinery scheduling at the intermediate blending component tanks into the production unit and product blending scheduling problems. The mathematical decompositions, such as Bender decomposition, Lagrangian decomposition, and bilevel decompositions, are another strategy based on the mathematical formulation of the problem. Bender decomposition, which is suitable for the problem with complicated variables, is applied to solve the stochastic programming problem of planning under uncertainty (Li, 2013; Yang and Barton, 2016). The Lagrangian decomposition, which is used for the problem with complicated constraints, is employed to solve the integration of production planning and scheduling problem (Li and Ierapetritou, 2010; Mouret et al., 2011). The bilevel decomposition is applied to the large-scale capacity planning problem (Iyer and Grossmann, 1998; Mitra et al., 2014) and the integration of planning and scheduling problems under uncertainties (Chu et al., 2015).

3 Process model

The process models are the fundamental parts of production planning and scheduling. In a traditional refinery, the flowsheet can be separated into the crude oil distillation, intermediate (e.g., reformer, cracker, hydrotreater), and blending processes. The additional processes, such as storage tanks, pipeline transfer, and utility systems, are the extra parts of a model. The nonlinear models are used to represent process models that have more flexibility and accuracy than simplified linear models (Siamizade, 2019). The process models used in the production planning and scheduling are traditionally based on the empirical correlation or regression of the rigorous model. The data-driven approach to build the process models, such as artificial neural network (ANN), surrogate (Slaback and Riggs, 2007), data-based nonlinear (Li et al., 2016), and piecewise linear (Gao et al., 2015) models, also has application in the production planning and scheduling problem.

3.1 CDU model

The CDU separates crude oil into intermediate streams called distillation cuts. The fixed yield model is the most simplified linear model, which cannot represent different operation modes. A swing-cut model was proposed by Zhang et al. (2001) to optimize the production planning and scheduling problem. The sizes of swing-cuts are predefined and can be cut into either of the adjacent distillation cuts to represent different operation modes. The swing-cut model has also been widely used in production planning through planning software (e.g., RPMS, PIMS). Some further improvements have been studied to introduce nonlinearity. Li et al. (2005) proposed a procedure to determine the optimal weight/volume transfer ratios of CDU using the true boiling point (TBP) data and the cut-points of the operation modes. The swing-cut model was applied to refinery production planning integrated with the fluidized-bed catalytic cracker and product blending models. Guerra and Le Roux (2011a; 2011b) used the swing-cut model based on volume transfer ratios with a bias correcting the yields. Menezes et al. (2013) improved the swing-cut model through microcuts and considering the varying qualities in the corresponding light and heavy parts of a swing-cut. Alattas et al. (2011) proposed a nonlinear CDU model named fractionation index model, which represents the CDU as a series of fractionation units. The fractionation index model was investigated in single- and multi-period production planning optimization (Alattas et al., 2012). The hybrid CDU model proposed by Fu and Mahalec (2015) used the feed TBP and operational variables to predict the TBP curves and bulk properties of the distillation cuts (Fu et al., 2016). Their study in refinery production planning (Fu et al., 2018) also revealed the accuracy and flexibility of the hybrid CDU model.

3.2 Intermediate process and blending model

The intermediate process units in a refinery usually have three main types: Reformer, cracker, and hydrotreater. The traditional models of the process units are fixed yield models, and the yields come from empirical or simulative values depending on different operational modes. Li et al. (2005) used a regression model of FCC to obtain the yields for production planning. Alhajri et al. (2008) employed simplified nonlinear process correlation models to predict product yields and properties in refinery planning optimizations. The correlation models for FCC are based on nonlinear regression of simulative data from a rigorous model. Guerra and Le Roux (2011a; 2011b) used nonlinear empirical models for the FCC to express the product yields and properties through the operating variables and feed properties. Gueddar and Dua (2011) built the ANN model of the CCR and the naphtha splitter units via a disaggregation–aggregation based approach in the production planning problem.

The blending models have been studied through blending scheduling problems, such as discrete- and continuous-time blending scheduling (Pinto et al., 2000; Glismann and Gruhn, 2001). The blending models considering different constraints in the industry, such as blending recipes, storage tanks, inventory management, and order delivery (Jia and Ierapetritou, 2003; Li et al., 2005; Méndez et al., 2006), make the models distinguishable. Li et al. (2009) proposed a slot-based continuous-time scheduling model for gasoline blending considering additional operations and policies, such as blender setup times and limited inventory of components.

3.3 Additional process model

The additional processes are the energy and transfer systems, for example, the steam system and heat exchange network providing the energy and pipelines and storage tanks serving the transfer of streams in a refinery. The coupling of additional processes with the entire refinery must be optimized together with planning and scheduling. Rejowski Jr and Pinto (2008) built a continuous-time scheduling model of multiproduct pipeline systems between the refineries and the depots. Zhang and Hua (2007) proposed a utility system model of energy utilization integrated with the processing system in a plant-wide multiperiod planning problem. Zhang and Rong (2008) built a fuel gas system model considering the storage capability in a multi-period scheduling problem of fuel gas operation in a refinery. van den Heever and Grossmann (2003) proposed the integration of production planning and scheduling of a hydrogen supply network involving the logistic decisions. Jiao et al. (2012a) built a discrete-time multi-period scheduling model of the hydrogen system in a refinery. Zhao et al. (2014; 2015) proposed a multi-period production planning model for the integrated optimization of refinery production and the utility system.

3.4 Supply chain model

A typical supply chain in the petroleum industry includes all the activities related to the production and processing of materials, such as crude procurement and storage logistics, transportation to the refineries, refinery operations, and distribution and delivery of its products (Shah et al., 2011). The complexity of supply chain models scales with the number of process units and nonlinear process models. Julka et al. (2002a; 2002b) proposed an agent-based supply chain management framework and studied its refinery application considering the crude selection and purchase. Neiro and Pinto (2004) extended the process unit models to the general model of supply chains. Yang et al. (2010) considered the operation mode changeover and yield fluctuations in a multiperiod supply chain optimization model. Some refinery models (Zhang and Hua, 2007; Gueddar and Dua, 2011; Zhao et al., 2014; 2015) can be treated as supply chain models that keep the major activities from the procurement to the operations and simplify the others. Slaback and Riggs (2007) adopted the surrogate model of the refinery-wide supply chain to approximate the physical properties of process models.

4 Planning and scheduling with uncertainty

The uncertainty evolved in production planning and scheduling can have a variety of representations that can be divided into three classes. The first class is the uncertainty of the volatile market, which comprises the price, supply and demand, policy, and environmental factors. The second class is the uncertainty of the properties of the streams, including raw materials and intermediate streams. The third class is the uncertainty of the process parameters, for instance, the fluctuations of the yields. These classes of uncertainty can be studied separately or simultaneously. Li et al. (2004) considered the uncertainty of the raw material and the product demand through the confidence level and fill rate, respectively. Risk management using various risk measures, such as financial risk (Barbaro and Bagajewicz, 2004), downside risk (Eppen et al., 1989), and conditional value-at-risk (Rockafellar and Uryasev, 2000), is an approach used to address the uncertainty in production planning and scheduling. Pongsakdi et al. (2006) considered the uncertainty in demand, market prices, raw material costs, and production yields in planning using financial risk. Park et al. (2010) chose the downside risk and regarded the price uncertainty of the crude oil and the products in refinery planning. Carneiro et al. (2010) adopted the conditional value-at-risk considering the uncertainty of the product demand and consumer budget. Ji et al. (2015) employed the operational and financial hedging strategy to deal with the uncertainty of crude oil prices in the crude oil procurement. The financial risk management approach is formulated as a scenario-based one- or two-stage stochastic programming to optimize the expected value of the objective function. Stochastic programming has also been used in other planning and scheduling problems, such as supply chain optimization with the uncertainty of product yields (Yang et al., 2010), integration of crude selection, and refinery optimization with the uncertainty of crude qualities (Yang and Barton, 2016).

The chance-constrained and robust optimization are two other approaches for optimization with uncertainty compared with stochastic programming. Chance-constrained optimization considers probabilistic constraints as part of the optimization problem. Yang et al. (2017) proposed a blending scheduling problem under the uncertainty of component qualities. The chance-constrained optimization has also been used in other production planning and scheduling problems, such as optimization of refinery hydrogen network with the uncertainty of hydrogen supply and demand (Jiao et al., 2012b) and multi-period planning with the uncertainty of component qualities (Jalanko and Mahalec, 2018). The robust optimization attempts to find a satisfying solution to the worst case provided by a bounded uncertainty set. Al-Qahtani and Elkamel (2010) performed robust optimization to address the multisite integration and coordination strategies in a network of petroleum refineries considering the uncertainty of the model parameters.

5 Virtual manufacturing of refinery

A virtual manufacturing system in a Chinese refinery is established by integrating the mechanism modeling, planning, scheduling, and unit optimization technologies to solve the process modeling and global and unit optimization problems. The architecture of the virtual manufacturing system is shown in Fig. 2. The technique structure can be divided into the following three layers: The visualization, application, and model layers. In the visualization layer, all the main units are rendered by three-dimensional modeling, providing a virtual reality environment. The application layer is based on core application software implementing several featured functions via the GUI and industrial data communication. The functions of the application layer comprise the following: 1) plant-wide simulation and validation, 2) sensitivity analysis and case studies, 3) unit operation optimization, and 4) plant-wide production planning optimization. In the model layer, the dedicated mechanism models of the primary units in the refinery are integrated with the two former layers providing simulation data. The models run parallel with the actual units and validate in real-time using the data collected from the actual process (from distributed control system (DCS), real-time database, or laboratory analysis database). The sensitivity analysis and operation optimization are functions for simulating operation modes and optimizing the operating conditions. The interaction of the application and model levels improves the understanding and operation of the process with highly accurate data, providing robust support for planning and scheduling. The optimization of planning and scheduling can be easily performed in this system with the mechanism models and the functions of the application layer. For instance, a successive linearized planning model is built in the system, and the parameters of the planning model can be updated by the mechanism models and operation optimization. Additionally, the monthly plan is divided into weekly plans that operate similarly to weekly schedules. Thus, planning and scheduling can generate realistic implementation schemes in the refinery. The function of plant-wide production planning optimization is further illustrated by some real industrial cases as follows.

The accuracy and feasibility are significantly improved by combining the mechanism model and decision-making application. This approach enables engineers to conduct planning and scheduling with additional profit. Several typical cases are generated from the virtual manufacturing system for regular planning. Case 1: A monthly planning optimization with the optimal operational parameters of the process provides an effective route for processing residual oil. The optimal plan decreases the capacity of the SDA unit and maximizes the capacity of the delayed coke unit. This plan aims to decrease the recycled heavy oil from the SDA to the RHT unit and simultaneously satisfy the demands of product oils. In this case, the recycled heavy oil can be lowered by 20 t/h and the energy cost is decreased by 486 kg EO/h. Case 2: Reorganization of the diesel resource at the plant-wide level. This case indicates the replacement of the diesel in the RHT feed with residue oil to increase the FCC capacity to produce additional diesel and gasoline. The removed diesel is sent to HCR and DHT units to maintain high quality. This case provides an effective way to transfer heavy oil to diesel and gasoline. Case 3: A combination of the process optimization with planning. The olefin derivatives, such as styrene, are considered high-value products in the Chinese market. Additional benzene from the aromatic process and olefin

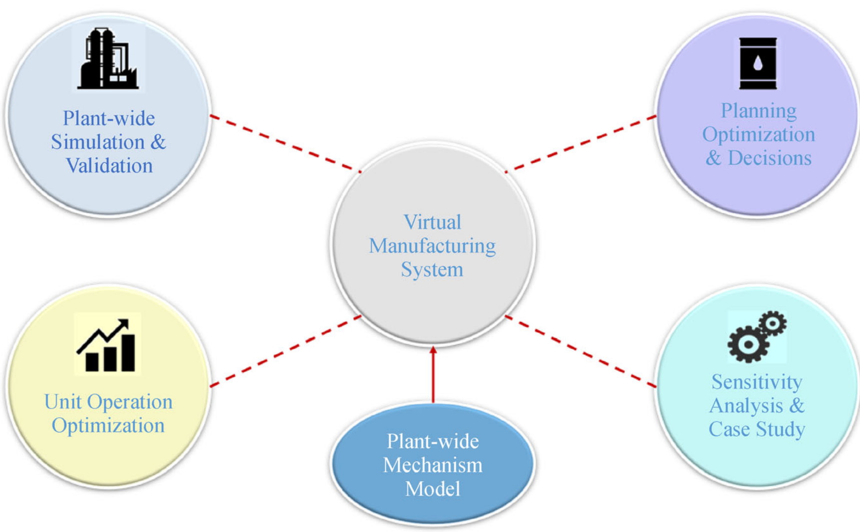

Fig. 2 Architecture of the virtual manufacturing system.

from FCC are needed to maximize the yield of styrene. In this case, benzene is sufficient, but ethylene is lacking because the ethylene cracking unit does not exist in this plant. Thus, the operation parameters must be optimized to maximize the ethylene yield of FCC by using the mechanism models. The plant-wide resources in PIMS, such as CCR feed, benzene, and production mode of styrene unit, are also optimized. Overall, styrene production can be increased by 100 ton/month, resulting in a considerable amount of profit. Except for the decision-making cases, the smart manufacturing system can also be used for real-time optimization. The process optimization for CCR, HCR, and CDU is currently implemented with advanced control. Such implementation helps engineers optimize the reaction temperature, pressure, and reflux ratio to gain additional valuable products and save energy.

According to statistics, engineers have used this system to generate more than 80 planning cases, 900 unit optimizing cases, and 1200 unit performance analyses per year from 2016. The total yield of the light product oil has increased by 2.8%, and the production loss rate has reduced by 0.04%, which can help the company increase the total profit of 1.316 billion yuan in three years. This reproducible and promotable smart manufacturing application is of considerable importance to the intelligent plant system, which also provides a successful example for smart process manufacturing.

6 Remaining challenges

Through the previous development of planning and scheduling optimization, the problem definition considers an increasing number of real industry constraints. The long-term and multiperiod models and complex process models, which rapidly increase the scale and complexity of the problem, become the decision requirements. The optimization under uncertainty remains the focus of risk management in refineries. All these challenges require the development of the optimization technique and highly efficient CPUs.

Some academic studies involving enterprise-wide optimization (Grossmann, 2005; 2012), molecular modeling and management (Hu et al., 2002), integration of production planning, scheduling, and process control (Santander et al., 2020), and integration of refining and petrochemical plant (Zhao et al., 2017) can still be improved for practical application. The production planning and scheduling considering the environmental factors, such as the corrosion effect (Kim et al., 2012), energy efficiency (Wu et al., 2017), and CO_2 emission reduction (Elkamel et al., 2008) in refineries, need additional attention.

The academic research on optimization of the refinery operations and strategies has achieved remarkable success, such as the development of rigorous and simplified process models, the improvement of planning and scheduling models, and the enhancement of large-scale MINLP algorithms. Nevertheless, the issue of building and simplifying the massive refinery unit models and optimizing the integrated refinery units in multilevel decisions remains complicated. For example, the three sub-problems (i.e., crude oil unloading and mixing, production operation scheduling, and product blending and delivering) of scheduling optimization are separately studied under specific assumptions. The scheduling strategy level of large refineries from the crude oil to the product blending scheduling has not been systematically studied. The rigorous process unit models with high accuracy remain complicated, which introduces computational complexity (e.g., large-scale problems and high nonlinearity) in the solution of the large-scale MINLP. Therefore, the simplified unit models are adopted considering the optimization efficiency, which causes deviations between the real operations and optimal results. However, the impact of the deviations has not been quantitatively described. Thus, guaranteeing the reliability and maintainability of the simplified model is difficult.

The models used in planning and scheduling are steady-state models. However, the resident time needed from crude to the final product is significant, and the switch of the unit operation modes is in the transient state, which needs the dynamic models. The research considering the switching transient state in the scheduling has just started. The latency of the streams in the overall process, which affects the scheduling of the overall refinery, has not been investigated.

The planning and scheduling problems are large-scale MINLP problems, especially in large refineries, which are optimized by the commercial solvers, such as BARON and ANTIGONE. Thus, the optimization consumes an immense amount of time. The utilization of the existing computational resources, such as cloud and distributed computing, is necessary to develop efficient solving algorithms and strategies.

7 Conclusions

Production planning and scheduling are crucial decision-making activities in a refinery. The decision optimization can maximize the profit and satisfy the constraints. Mathematical programming has long been adopted in production planning and scheduling. Following the development of the optimization technique, an increasing number of constraints and complexity can be added into the decision-making consideration, thus providing a realistic application. The reaming challenges focus on developing process models and optimization algorithms that can utilize the computational resources and minimize the deviations between the optimal solution and real operations.

References

Al-Qahtani K, Elkamel A (2010). Robust planning of multisite refinery networks: Optimization under uncertainty. Computers & Chemical Engineering, 34(6): 985–995

Alattas A M, Grossmann I E, Palou-Rivera I (2011). Integration of nonlinear crude distillation unit models in refinery planning optimization. Industrial & Engineering Chemistry Research, 50 (11): 6860–6870

Alattas A M, Grossmann I E, Palou-Rivera I (2012). Refinery production planning: Multiperiod MINLP with nonlinear CDU model. Industrial & Engineering Chemistry Research, 51(39): 12852–12861

Alhajri I, Elkamel A, Albahri T, Douglas P L (2008). A nonlinear programming model for refinery planning and optimisation with rigorous process models and product quality specifications. International Journal of Oil, Gas and Coal Technology, 1(3): 283–307

Barbaro A, Bagajewicz M J (2004). Managing financial risk in planning under uncertainty. AIChE Journal, 50(5): 963–989

Carneiro M C, Ribas G P, Hamacher S (2010). Risk management in the oil supply chain: A CVaR approach. Industrial & Engineering Chemistry Research, 49(7): 3286–3294

Castillo P A C, Castro P M, Mahalec V (2017a). Global optimization of nonlinear blend-scheduling problems. Engineering, 3(2): 188–201

Castillo P C, Castro P M, Mahalec V (2017b). Global optimization algorithm for large-scale refinery planning models with bilinear terms. Industrial & Engineering Chemistry Research, 56(2): 530–548

Chu Y, You F, Wassick J M, Agarwal A (2015). Integrated planning and scheduling under production uncertainties: Bi-level model formulation and hybrid solution method. Computers & Chemical Engineering, 72: 255–272

Drud A S (1994). CONOPT—A large-scale GRG code. ORSA Journal on Computing, 6(2): 207–216

Elkamel A, Ba-Shammakh M, Douglas P, Croiset E (2008). An optimization approach for integrating planning and CO_2 emission reduction in the petroleum refining industry. Industrial & Engineering Chemistry Research, 47(3): 760–776

Eppen G D, Martin R K, Schrage L (1989). A scenario approach to capacity planning. Operations Research, 37(4): 517–527

Fu G, Castillo P A C, Mahalec V (2018). Impact of crude distillation unit model accuracy on refinery production planning. Frontiers of Engineering Management, 5(2): 195–201

Fu G, Mahalec V (2015). Comparison of methods for computing crude distillation product properties in production planning and scheduling. Industrial & Engineering Chemistry Research, 54(45): 11371–11382

Fu G, Sanchez Y, Mahalec V (2016). Hybrid model for optimization of crude oil distillation units. AIChE Journal, 62(4): 1065–1078

Gao X, Jiang Y, Chen T, Huang D (2015). Optimizing scheduling of refinery operations based on piecewise linear models. Computers & Chemical Engineering, 75: 105–119

Glismann K, Gruhn G (2001). Short-term scheduling and recipe optimization of blending processes. Computers & Chemical Engineering, 25(4–6): 627–634

Grossmann I E (2005). Enterprise-wide optimization: A new frontier in process systems engineering. AIChE Journal, 51(7): 1846–1857

Grossmann I E (2012). Advances in mathematical programming models for enterprise-wide optimization. Computers & Chemical Engineering, 47: 2–18

Grossmann I E, Raman R (2020). DICOPT. Available at: gams.com/latest/docs

Gueddar T, Dua V (2011). Disaggregation–aggregation based model reduction for refinery-wide optimization. Computers & Chemical Engineering, 35(9): 1838–1856

Guerra O J, Le Roux G A C (2011a). Improvements in petroleum refinery planning: 1. Formulation of process models. Industrial & Engineering Chemistry Research, 50(23): 13403–13418

Guerra O J, Le Roux G A C (2011b). Improvements in petroleum refinery planning: 2. Case studies. Industrial & Engineering Chemistry Research, 50(23): 13419–13426

Hou Y, Wu N, Zhou M, Li Z (2017). Pareto-optimization for scheduling of crude oil operations in refinery via genetic algorithm. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 47(3): 517–530

Hu S, Towler G, Zhu F X X (2002). Combine molecular modeling with optimization to stretch refinery operation. Industrial & Engineering Chemistry Research, 41(4): 825–841

Iyer R R, Grossmann I E (1998). A bilevel decomposition algorithm for long-range planning of process networks. Industrial & Engineering Chemistry Research, 37(2): 474–481

Jalanko M, Mahalec V (2018). Supply-demand pinch based methodology for multi-period planning under uncertainty in components qualities with application to gasoline blend planning. Computers & Chemical Engineering, 119: 425–438

Ji X, Huang S, Grossmann I E (2015). Integrated operational and financial hedging for risk management in crude oil procurement. Industrial & Engineering Chemistry Research, 54(37): 9191–9201

Jia Z, Ierapetritou M (2003). Mixed-integer linear programming model for gasoline blending and distribution scheduling. Industrial & Engineering Chemistry Research, 42(4): 825–835

Jia Z, Ierapetritou M (2004). Efficient short-term scheduling of refinery operations based on a continuous time formulation. Computers & Chemical Engineering, 28(6–7): 1001–1019

Jia Z, Ierapetritou M, Kelly J D (2003). Refinery short-term scheduling using continuous time formulation: Crude-oil operations. Industrial & Engineering Chemistry Research, 42(13): 3085–3097

Jiao Y, Su H, Hou W, Liao Z (2012a). A multiperiod optimization model for hydrogen system scheduling in refinery. Industrial & Engineering Chemistry Research, 51(17): 6085–6098

Jiao Y, Su H, Hou W, Liao Z (2012b). Optimization of refinery hydrogen network based on chance constrained programming. Chemical Engineering Research & Design, 90(10): 1553–1567

Joly M, Moro L F L, Pinto J M (2002). Planning and scheduling for petroleum refineries using mathematical programming. Brazilian Journal of Chemical Engineering, 19(2): 207–228

Julka N, Karimi I, Srinivasan R (2002a). Agent-based supply chain management-2: A refinery application. Computers & Chemical Engineering, 26(12): 1771–1781

Julka N, Srinivasan R, Karimi I (2002b). Agent-based supply chain management-1: Framework. Computers & Chemical Engineering, 26 (12): 1755–1769

Karuppiah R, Furman K C, Grossmann I E (2008). Global optimization for scheduling refinery crude oil operations. Computers & Chemical

Engineering, 32(11): 2745–2766
Kim J, Tak K, Moon I (2012). Optimization of procurement and production planning model in refinery processes considering corrosion effect. Industrial & Engineering Chemistry Research, 51 (30): 10191–10200
Lee H, Pinto J M, Grossmann I E, Park S (1996). Mixed-integer linear programming model for refinery short-term scheduling of crude oil unloading with inventory management. Industrial & Engineering Chemistry Research, 35(5): 1630–1641
Li J, Karimi I A, Srinivasan R (2009). Recipe determination and scheduling of gasoline blending operations. AIChE Journal, 56(2): 441–465
Li J, Xiao X, Boukouvala F, Floudas C A, Zhao B, Du G, Su X, Liu H (2016). Data-driven mathematical modeling and global optimization framework for entire petrochemical planning operations. AIChE Journal, 62(9): 3020–3040
Li W, Hui C W, Li A (2005). Integrating CDU, FCC and product blending models into refinery planning. Computers & Chemical Engineering, 29(9): 2010–2028
Li W, Hui C W, Li P, Li A X (2004). Refinery planning under uncertainty. Industrial & Engineering Chemistry Research, 43(21): 6742–6755
Li X (2013). Parallel nonconvex generalized Benders decomposition for natural gas production network planning under uncertainty. Computers & Chemical Engineering, 55: 97–108
Li Z, Ierapetritou M G (2010). Production planning and scheduling integration through augmented Lagrangian optimization. Computers & Chemical Engineering, 34(6): 996–1006
Méndez C A, Grossmann I E, Harjunkoski I, Kaboré P (2006). A simultaneous optimization approach for off-line blending and scheduling of oil-refinery operations. Computers & Chemical Engineering, 30(4): 614–634
Menezes B C, Kelly J D, Grossmann I E (2013). Improved swing-cut modeling for planning and scheduling of oil-refinery distillation units. Industrial & Engineering Chemistry Research, 52(51): 18324–18333
Menezes B C, Kelly J D, Grossmann I E, Vazacopoulos A (2015). Generalized capital investment planning of oil-refineries using MILP and sequence-dependent setups. Computers & Chemical Engineering, 80: 140–154
Misener R, Floudas C A (2014). ANTIGONE: Algorithms for continuous/integer global optimization of nonlinear equations. Journal of Global Optimization, 59(2–3): 503–526
Mitra S, Pinto J M, Grossmann I E (2014). Optimal multi-scale capacity planning for power-intensive continuous processes under time-sensitive electricity prices and demand uncertainty. Part II: Enhanced hybrid bi-level decomposition. Computers & Chemical Engineering, 65: 102–111
Moro L F L, Zanin A C, Pinto J M (1998). A planning model for refinery diesel production. Computers & Chemical Engineering, 22: S1039–S1042
Mouret S, Grossmann I E, Pestiaux P (2009). A novel priority-slot based continuous-time formulation for crude-oil scheduling problems. Industrial & Engineering Chemistry Research, 48(18): 8515–8528
Mouret S, Grossmann I E, Pestiaux P (2011). A new Lagrangian decomposition approach applied to the integration of refinery planning and crude-oil scheduling. Computers & Chemical Engineering, 35(12): 2750–2766
Neiro S M S, Pinto J M (2004). A general modeling framework for the operational planning of petroleum supply chains. Computers & Chemical Engineering, 28(6–7): 871–896
Neiro S M S, Pinto J M (2005). Multiperiod optimization for production planning of petroleum refineries. Chemical Engineering Communications, 192(1): 62–88
Park J, Park S, Yun C, Kim Y (2010). Integrated model for financial risk management in refinery planning. Industrial & Engineering Chemistry Research, 49(1): 374–380
Pinto J M, Joly M, Moro L F L (2000). Planning and scheduling models for refinery operations. Computers & Chemical Engineering, 24(9–10): 2259–2276
Pongsakdi A, Rangsunvigit P, Siemanond K, Bagajewicz M J (2006). Financial risk management in the planning of refinery operations. International Journal of Production Economics, 103(1): 64–86
Rejowski Jr R, Pinto J M (2003). Scheduling of a multiproduct pipeline system. Computers & Chemical Engineering, 27(8–9): 1229–1246
Rejowski Jr R, Pinto J M (2004). Efficient MILP formulations and valid cuts for multiproduct pipeline scheduling. Computers & Chemical Engineering, 28(8): 1511–1528
Rejowski Jr R, Pinto J M (2008). A novel continuous time representation for the scheduling of pipeline systems with pumping yield rate constraints. Computers & Chemical Engineering, 32(4–5): 1042–1066
Rockafellar R T, Uryasev S (2000). Optimization of conditional value-at-risk. Journal of Risk, 2(3): 21–41
Sahinidis N V (1996). BARON: A general purpose global optimization software package. Journal of Global Optimization, 8(2): 201–205
Santander O, Betts C L, Archer E E, Baldea M (2020). On the interaction and integration of production planning and (advanced) process control. Computers & Chemical Engineering, 133: 106627
Shah N, Saharidis G K D, Jia Z, Ierapetritou M G (2009). Centralized-decentralized optimization for refinery scheduling. Computers & Chemical Engineering, 33(12): 2091–2105
Shah N K, Ierapetritou M G (2011). Short-term scheduling of a large-scale oil-refinery operations: Incorporating logistics details. AIChE Journal, 57(6): 1570–1584
Shah N K, Li Z, Ierapetritou M G (2011). Petroleum refining operations: Key issues, advances, and opportunities. Industrial & Engineering Chemistry Research, 50(3): 1161–1170
Shah N K, Sahay N, Ierapetritou M G (2015). Efficient decomposition approach for large-scale refinery scheduling. Industrial & Engineering Chemistry Research, 54(41): 9964–9991
Siamizade M R (2019). Global optimization of refinery-wide production planning with highly nonlinear unit models. Industrial & Engineering Chemistry Research, 58(24): 10437–10454
Simao L M, Dias D M, Pacheco M A C (2007). Refinery scheduling optimization using genetic algorithms and cooperative coevolution. In: IEEE Symposium on Computational Intelligence in Scheduling. Honolulu, HI, 151–158
Slaback D D, Riggs J B (2007). The inside-out approach to refinery-wide optimization. Industrial & Engineering Chemistry Research, 46(13): 4645–4653
van den Heever S A, Grossmann I E (2003). A strategy for the

integration of production planning and reactive scheduling in the optimization of a hydrogen supply network. Computers & Chemical Engineering, 27(12): 1813–1839

Wu N, Li Z, Qu T (2017). Energy efficiency optimization in scheduling crude oil operations of refinery based on linear programming. Journal of Cleaner Production, 166: 49–57

Yang J, Gu H, Rong G (2010). Supply chain optimization for refinery with considerations of operation mode changeover and yield fluctuations. Industrial & Engineering Chemistry Research, 49(1): 276–287

Yang Y, Barton P I (2016). Integrated crude selection and refinery optimization under uncertainty. AIChE Journal, 62(4): 1038–1053

Yang Y, Vayanos P, Barton P I (2017). Chance-constrained optimization for refinery blend planning under uncertainty. Industrial & Engineering Chemistry Research, 56(42): 12139–12150

You F, Grossmann I E, Wassick J M (2011). Multisite capacity, production, and distribution planning with reactor modifications: MILP model, bilevel decomposition algorithm versus Lagrangean decomposition scheme. Industrial & Engineering Chemistry Research, 50(9): 4831–4849

Zhang B J, Hua B (2007). Effective MILP model for oil refinery-wide production planning and better energy utilization. Journal of Cleaner Production, 15(5): 439–448

Zhang J, Zhu X X, Towler G P (2001). A level-by-level debottlenecking approach in refinery operation. Industrial & Engineering Chemistry Research, 40(6): 1528–1540

Zhang J D, Rong G (2008). An MILP model for multi-period optimization of fuel gas system scheduling in refinery and its marginal value analysis. Chemical Engineering Research & Design, 86(2): 141–151

Zhao H, Ierapetritou M G, Shah N K, Rong G (2017). Integrated model of refining and petrochemical plant for enterprise-wide optimization. Computers & Chemical Engineering, 97: 194–207

Zhao H, Rong G, Feng Y (2014). Multiperiod planning model for integrated optimization of a refinery production and utility system. Industrial & Engineering Chemistry Research, 53(41): 16107–16122

Zhao H, Rong G, Feng Y (2015). Effective solution approach for integrated optimization models of refinery production and utility system. Industrial & Engineering Chemistry Research, 54(37): 9238–9250