A Data-Driven Rolling-Horizon Online Scheduling Model for Diesel Production of a Real-World Refinery

Cao Cuiwen and Gu Xingsheng
Key Laboratory of Advanced Control and Optimization for Chemical Processes, Ministry of Education, East China University of Science and Technology, Shanghai 200237, P.R. China

Xin Zhong
State Key Laboratory of Chemical Engineering, School of Chemical Engineering, East China University of Science and Technology, Shanghai 200237, P.R. China

DOI 10.1002/aic.13895
Published online September 28, 2012 in Wiley Online Library (wileyonlinelibrary.com).

A rolling-horizon optimal control strategy is developed to solve the online scheduling problem for a real-world refinery diesel production based on a data-driven model. A mixed-integer nonlinear programming (MINLP) scheduling model considering the implementation of nonlinear blending quality relations and quantity conservation principles is developed. The data variations which drive the MINLP model come from different sources of certain and uncertain events. The scheduling time horizon is divided into equivalent discrete time intervals, which describe regular production and continuous time intervals which represent the beginning and ending time of expected and unexpected events that are not restricted to the boundaries of discrete time intervals. This rolling-horizon optimal control strategy ensures the dimension of the diesel online scheduling model can be accepted in industry use. LINGO is selected to be the solution software. Finally, the daily diesel scheduling scheme of one entire month for a real-world refinery is effectively solved. © 2012 American Institute of Chemical Engineers *AIChE J,* 59: 1160–1174, 2013
Keywords: rolling-horizon optimal control strategy, data-driven, online scheduling, diesel production, uncertainty

Introduction

In a typical refinery, a series of operations for transforming crude oils into higher value end products (gasoline, jet fuel, diesel, etc.) begin with crude oil unloading, mixing, and transferring, followed by the distillation process which separates the charged oils into consecutive lighter and heavier fractions with different boiling points. Most of the distillates obtained need to be further processed via vacuum distillation units, fluid catalytic cracking units, coking units or hydrotreating units, etc. Finally, different intermediate products and additives are mixed to produce the final products. Planning determines the volumes of different feed streams, the amounts of intermediate or final products over one or several months. Scheduling deals with the short-term (7 or 10 days, or online) refinery operations to implement the plan.

Most of the commercial tools such as Aspen Blend, Aspen PIMS—MBO, Aspen Orion-XT, and Honeywell's BLEND are restricted to product-blending planning problems and do not involve detailed scheduling decisions.[1,2] There are three main obstacles in dealing with refinery scheduling: the lack of general models to address different refinery particularities, the low availability of effective and robust tools capable of dealing with uncertainties, and the limitations in computing technology for large-scale combinatorial optimization problems.

Since 1990s, many researchers have put their efforts on discrete plants or batch plants scheduling problems. Much less work has been devoted to continuous plants.[2] Mixed-integer linear programming (MILP) and MINLP models were developed to solve crude oil short-term scheduling problem.[3–5] Moro et al.[6] presented a general diesel nonlinear programming (NLP) planning model which can implement nonlinear process as well as blending relations. Pinto et al.[3] used MINLP models for scheduling fuel oil and asphalt production. All these models use discrete-time formulations that split the time horizon into equal intervals and usually require large numbers of binary variables and constraints.

In recent years, mathematical models for refinery scheduling operations emphasize on continuous-time formulations. Glismann and Gruhn[7] proposed a two-level optimization approach to simultaneously solve both recipe optimization and scheduling problem. The first level is an NLP recipe model, the second is an MILP model based on resource-task network (RTN) time representation. Pinto et al.[3] extended the basic general modeling idea of Moro et al.[6] to solve the liquefied petroleum gas (LPG) scheduling problem. They adopted time-slot representation in their formulations. Jia et al.[8] presented a strategy to decompose the overall refinery scheduling operations into three parts. The first part studies the crude oil unloading, mixing, transferring and multilevel

Correspondence concerning this article should be addressed to C. Cuiwen at caocuiwen@ecust.edu.cn.

crude oil inventory control process. The second part deals with fractionation, reaction units scheduling and a variety of intermediate product tanks control. The third part involves the finished product blending and distributing process. A set of MILP models was developed to solve each of their subproblems based on state-task network (STN) time representation. Mendez et al.[2] provided a novel iterative MILP formulation for solving simultaneously gasoline short-term blending and scheduling problem. The model is based on time-slot domain representation. All streams' properties are assumed to have linear relationships, whereas in real world they have nonlinear characteristics.

There is no doubt that continuous-time representation can reduce the dimension of scheduling models especially because events such as the beginning and ending time of a task are not restricted to the boundaries of discrete time intervals. However, the discrete-time representation still has some advantages. One of them is that discrete-time representation provides a relatively straightforward and simple time structure for all operations. Detailed comparison between continuous-time and discrete-time representation of scheduling problems can be found in the review work of Floudas and Lin.[9]

Until now, all the discussions mentioned previously adopt deterministic mathematical programming methods to solve the refinery scheduling problem. The data in their models are assumed to be deterministic. In real world, the situations are uncertain due to the dynamic nature of the environment. The variations of some parameters, such as streams qualities (for example, sulfur content or acidity value), yield levels, changeovers of crude oils or intermediate distillates and some unexpected events, etc., are of great importance in short-term scheduling operation decisions. Nowadays, most refinery schedulers consider the impacts of these important events to make decisions based on their years of experience.

Floudas and Lin[9] divided existing approaches in chemical process scheduling under uncertainty into two groups: stochastic scheduling and reactive scheduling. The similar idea was also proposed by Li and Ierapetritou,[10,11] where the stochastic scheduling was enriched as preventive scheduling, which includes stochastic scheduling, fuzzy programming method, robust optimization method and parametric programming method. Stochastic scheduling methods deal with optimization problems whose parameters take values from assumed discrete/continuous probability distributions which usually cannot reflect real-world online variations.[12] There are two types of solution methods: the chance constraint programming[13–16] and the decomposition based stochastic programming.[17–25] Fuzzy programming[26–29] assumes that uncertain parameters in a scheduling model are fuzzy numbers defined on a fuzzy set associated with a membership function. Robust optimization[30–33] aims at building the preventive schedule to minimize the effects of disruptions on the performance measure.[11] Parametric programming method[11,34] provides an effective way in mapping the uncertainties arisen from petrochemical scheduling problems to optimal solution alternatives. Reactive scheduling method modifies a schedule at/right before the uncertain operations, such as rush order arrivals, order cancellations, machine breakdowns, or other occurrence of unexpected events. Many researchers[35–41] use this type of methodology to solve batch plants scheduling problem under uncertainties. Among them, Rodrigues et al.[35] presented a reactive scheduling model based on STN. A rolling-horizon idea is first utilized to obtain short response time. Li[42] developed a just-in-time operation simulation environment based on a rolling-horizon control scheme to solve refinery inventory and production management plan from a supply chain perspective.

Model predictive control or rolling-horizon control has achieved great success for robust multivariable control in process industries, and has turned into one of the preferred algorithms in real-time applications.[42] Enlightened by the basic sequence optimal control move strategy of model predictive control and the reactive scheduling methodology, we develop a novel data-driven rolling-horizon optimal control strategy to solve the diesel production online scheduling problem under the situation when both certain and uncertain events coexist. In fact, no matter what kinds of uncertain events happen, the differences appear as data variations in the model. If these vital changes could be acquired just before the execution of final operations, online scheduling schema can be made with the help of the latest updated data, effective computing tools, and the general model of disposing different refinery particularities. To our knowledge, there is no record on the use of this data-driven rolling-horizon control strategy to deal with diesel online scheduling problem. Our scheduling framework is based on the general framework of nonlinear planning problem proposed by Moro et al.[6] that allows the implementation of nonlinear process and blending relations. We extend their model to complex MINLP formulations based on quantity conservation principles and quality constitutive relations suggested by Hou.[43] Then, we roll this model according to equivalent discrete time intervals which describe the regular production and continuous time intervals which represent the beginning and ending time of expected and unexpected events that are not restricted to the boundaries of discrete time intervals. LINGO 11.0 is selected to be the solution software. The proposed method is proved to be effective in generating 1 month's daily scheduling scheme for diesel production of a real-world refinery.

This article is organized as follows: in the Problem Definitions section, the problem statement, assumptions, modeling and optimization strategy are introduced; in the Mathematical Model section, the detail mathematical formulations of the MINLP diesel online scheduling model and the data-driven rolling-horizon optimal control strategy are presented; in A Real-World Refinery Application section, a real-world refinery diesel production application and the calculation results are presented; the last section is the conclusion.

Problem Definitions

Problem statements

Due to the current unsteady supply of crude oil, intense time pressure and low-inventory flexibility, most of the diesel blending components are not stored in component tanks and are instead blended in online blend units. Few components are stored in intermediate storage tanks to be used whenever necessary. This situation means that this production process involves both continuous and batch operations, and the online scheduling is the most important task that should be solved before the final blending process start. Nowadays, this kind of task can only be adequately performed by experienced schedulers, since only linear programming calculations are available as supporting tools. In order to ensure the qualities of the final products, the schedulers must allow significant quality giveaways, which negatively affect the profitability.

Two issues need to be taken into consideration in our diesel scheduling model.

The first one concerns with the production quality constraints. Final product qualities are predicted through complex correlations that depend on the properties of components used in the blend. Linear and nonlinear correlations coexist in these formulations or experimental data tables.

The second issue is related to the aspect of production logistics. Under given parameters and assumptions, how to decide the time interval representation for the parameters and variables of the scheduling model when certain and uncertainty events coexist is first considered. After that, how to find the optimal solution for the flow rates of all component and final product streams is to be solved.

The general diesel scheduling process corresponds to a large-scale, multistage, multiproduct complex system where discrete and continuous time intervals coexist. The online diesel scheduling problem under study is specified as later.

Givens and assumptions:

1. A predefined online scheduling horizon of 1 day which describes the regular production. If some certain events, such as changeovers of crude oils, and uncertain events, such as unexpected machine breakdown, components taken away to produce rush orders, unsteady supplies of crude oils, etc., do not occur exactly on the boundaries of the day, then continuous time intervals which represent the start and end time of these events are used;
2. A set of crude oil supplies with given flow rates;
3. All the feed streams except crude oil supplies are mixed in a given proportion before entering a unit and this mixing is instantaneous;
4. Each product stream is split after leaving a unit for the reason that the product stream may be sent to several units;
5. Yield level (%) obtained from plant can be used to determine intermediate product flow rates;
6. A set of intermediate components and their property indices from the LAN (local area network) of a refinery can be obtained online;
7. A set of final product blending tanks working in parallel with maximum capacity of disposing a single day's full-load production for a refinery;
8. Several intermediate storage tanks which are used for storing the streams that could not be consumed completely within the scheduling time horizon;
9. A set of final products with predefined minimum and maximum quality specifications;
10. All final products are assumed to be sold out every day. The final products storage tanks and their maximum capacity restrictions are not be taken into consideration;
11. Energy balances are not included in this model;
12. The mass balance of the units concerned may not be satisfied since not all streams are bound for diesel production. The streams that cannot produce diesel oil are not included in the scheduling model. Because different refineries may have different process flows, we take two processing units of the real-world refinery for example. For the vacuum distillation unit of 1# crude oil distillation unit (CDU1), there is five streams generated in it: the vacuum gas oil, the light vacuum distillate, the medium vacuum distillate, the heavy vacuum distillate and the vacuum residue. The vacuum gas oil and the light vacuum distillate are used for final diesel product blending; the medium vacuum distillate and the heavy vacuum distillate will be transferred to solvent dewaxing units; the vacuum residue will be sent to propane deasphalting units and asphalt plants. The latter three distillates cannot be used in diesel production. A hydrotreating unit generates five streams: the light distillate, the light hydrotreated oil, the medium hydrotreated oil, the heavy hydrotreated oil and the high-viscosity hydrotreated oil. The light distillate is used for final diesel product blending. The latter four distillates are transferred to solvent dewaxing units to be further processed and cannot be used in diesel production.

Determine:

1. The flow rates of all streams that are concerned with diesel production leaving upstream units and reaching downstream units during the scheduling time horizon;
2. All product flow rates during the scheduling time horizon;
3. All product properties during the scheduling time horizon;
4. The types and amounts of the unused components during the scheduling time horizon.

Objective:

The objective is to maximize the amount of all final products under current available resources, whereas at the same time satisfying the process constraints, operations constraints, and quality specifications.

Modeling and optimization strategies

In model predictive control, which uses the rolling-horizon control scheme, current and historical measurements are used to predict the system behavior at a future time instant. A sequence of control moves is then selected to optimize a relevant objective function whereas satisfying system constraints. At the next period, the calculation process is repeated using updated system state parameters. Enlightened by this rolling-horizon control scheme, we developed the data-driven rolling-horizon online diesel scheduling model addressed in this article.

The nonlinear planning model originated by Moro et al.[6] is first selected as the base of our scheduling model. Afterward it is expanded and modified into a complex MINLP one based on quantity conservation principles, constitutive relations, and quality constraints provided by Hou.[43] Expected and unexpected events are described as data variations in the model. After that, we drive this model according to equivalent discrete time intervals (1 day), representing regular production and continuous time intervals, representing the start and end time of certain and uncertain events that are not exactly on the boundaries of any given day. Under this situation, two or more blending recipes and optimal scheduling operations should be provided in 1 day. This data-driven rolling-horizon optimal control strategy ensures that the size of the diesel scheduling model is acceptable in terms of computing time requirements for industrial online use. LINGO 11.0 was selected as the solution software, and its MINLP solver, based on Branch and Bound algorithm, was used to optimize the model, whose formulation is detailed in the following sections.

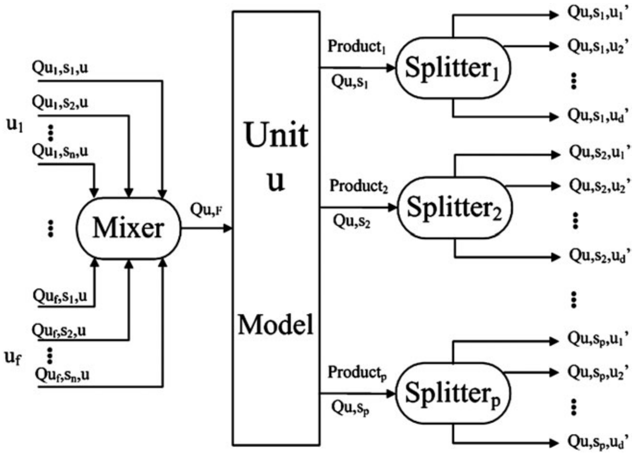

Figure 1. Typical process unit.

Mathematical Model

Mixed-integer nonlinear programming online scheduling model for diesel production

Moro et al.[6] presented a nonlinear planning model framework for refinery production. The model relies on a general representation for the refinery process units as shown in Figure 1. It describes a typical processing unit u, which is represented by the following equations.[6]

Feed flow rate:

$$Q_{u,F} = \sum_{u' \in U_u} \sum_{s \in S_{u',u}} Q_{u',s,u} \tag{a1}$$

Feed properties:

$$P_{u,F,j} = f_j(Q_{u',s,u}, P_{u',s,j}) \quad u' \in \mathbf{U}_u\,,\ \ s \in \mathbf{S}_{u',u}\,,\ \ j \in \mathbf{J}_s \tag{a2}$$

Total flow rate of each product stream:

$$Q_{u,s} = f(Q_{u,F}, P_{u,F,j}, \mathbf{V}_u) \quad s \in \mathbf{S}_U\,,\ \ j \in \mathbf{J}_F \tag{a3}$$

Unit product stream properties:

$$P_{u,s,j} = f_j(P_{u,F,j}, \mathbf{V}_u) \quad s \in \mathbf{S}_U\,,\ \ j \in \mathbf{J}_s \tag{a4}$$

Product streams flow rates (splitter):

$$Q_{u,s} = \sum_{u' \in \mathbf{U}_{s,u}} Q_{u,s,u'} \quad s \in \mathbf{S}_U \tag{a5}$$

$\mathbf{J}_F$ is the set of properties defined for the feed of unit u, $\mathbf{J}_s$ is the set of properties defined for stream s, $\mathbf{S}_{u',u}$ is the set of streams leaving unit u' and reaching u, $\mathbf{S}_U$ is the set of streams generated in unit u, $\mathbf{U}_u$ is the set of units whose destination is u, $\mathbf{V}_u$ is the set of operating variables defined for unit u, $\mathbf{U}_{s,u}$ is the set of units fed from the stream s produced in unit u; $P_{u,s,j}$ is the property j of stream s in unit u, $Q_{u,s}$ is the flow rate of stream s in unit u,$Q_{u',s,u}$ is the flow rate of stream s leaving unit u' ($\in \mathbf{U}_u$) and reaching unit u, is the flow rate of stream s leaving the unit u and reaching units u' ($\in \mathbf{U}_{s,u}$).

Equations a1 and a2 represent the mixing of the feed streams. They are defined by the sets $\mathbf{U}_u$ and $\mathbf{S}_{u',u}$ which denote the units u' whose destination is u and the streams leaving unit u' whose destination is unit u, respectively. The properties of the resulting feed stream are nonlinear functions of the entering feed streams and thus each property $j \in \mathbf{J}_s$. The process model is defined in Eqs. a3 and a4, which relate the product flow rate and properties to the flow rate and properties of the feed stream and also to the operating variables. They assumed that all the feed streams are mixed before entering a unit. Analogously, since a product stream may be sent to several units, it is assumed that each stream is split after leaving the unit. The unit balance is not satisfied since not all streams are bound for diesel production.

We adapted this general description of Moro et al.[6] to our diesel online scheduling model. Generally, diesel production process relates to crude distillation units (CDUs), vacuum distillation units, fluid catalytic cracking units, coking units, hydrotreating units, storage tanks of intermediate components, and diesel pipe blenders or blending tanks. Every unit participating in final blend is defined as the typical process unit as in Figure 1 and is included in our model. If any unit has not operated at some time, its parameters are set as zeros. This method assures that our model is generic enough to address different refinery particularities.

Considering the long-term shortage for diesel products in the real-world refinery's consumer market, the objective function of our MINLP model is to maximize the sum of the flow rates of all final products at scheduling time horizon t. The detailed mathematical formulations are as follows.

Objective:

$$Max \quad \sum_{j=1}^{n} QP_{j,t} \tag{1}$$

Subject to:

Quantity conservation constraints:

The mass balance is imposed in each of the diesel product streams which is either sent to the final product pool or sent to another processing unit. As mentioned in "*Problem statements*" of Problem Definitions section, the unit balance is not satisfied since not all streams are bound for diesel production.

Equation 2 states that the feed flow rate of unit u (after its mixer) at time t equals the sum of the flow rates of all the streams leaving units u' at time t. The destination of all the units u' is u

$$QF_{u,t} = \sum_{u' \in \mathbf{U}_{u,t}} \sum_{s \in \mathbf{S}_{u',u,t}} Q_{u',s,u,t} \tag{2}$$

Equation 3 indicates the feed flow rate of unit u at time t should be less than the maximum feed flow rate capacity

$$QF_{u,t} < QF_{u-\max} \tag{3}$$

Equation 4 states that the flow rate of stream s generated in unit u at time t is equal to the feed flow rate of unit u times the yield level (%) of the stream s at time t. $Q_{u,s,t}$ can also be measured directly online

$$Q_{u,s,t} = d_{u,s,t} \cdot QF_{u,t}, \quad s \in \mathbf{S}_{u,t} \tag{4}$$

Equation 5 represents the flow rate of stream s generated in unit u at time t, which is equal to the sum of each branch stream feeding units $u'(\in \mathbf{U}_{s,u,t})$ at time t (including those streams unused and stored in intermediate tanks)

$$Q_{u,s,t} = \sum_{u' \in \mathbf{U}_{s,u,t}} Q_{u,s,u',t} \tag{5}$$

If an intermediate stream involved in the scheduling model is not used for diesel production at a given time interval, due to some unexpected event, such as a machine breakdown or the routing of this stream to produce other products demanded by rush orders, etc., its flow rate is set as zero. If an intermediate stream cannot be completely consumed at a given time interval, its surplus amount is stored in an intermediate tank. If the objective is maximum profit, or the storage capacities of final product tanks are limited, each of the intermediate streams in the scheduling model should be provided with an intermediate tank. Under our objective of maximizing the yields of final products, only inferior streams are left. The types and the quantities of the remaining streams are computed online.

Because the same stream of the same processing unit may be generated from different crude oils, the properties of the relevant intermediate tank vary with the changeovers of crude oils and not all of them have linear relationships. To reduce the times of rechecking the qualities of every intermediate tank at each of the time intervals, a temporary blending tank which contains one type of remaining streams or all of the remaining streams at one previous time interval is used to take part in the final blending process at the present time period. New streams cannot enter the tank until it is empty. Which type of the remaining streams could be selected is computed online. Except the remaining streams in the temporary blending tank, the others are stored in intermediate tanks and cannot be put to use until better crude oils come. The material balance equations that connects previous time period to present time period of intermediate tanks does not have the usual purpose, so they are not listed in our scheduling model.

Quality constitutive relations constraints:

Equation 6 expresses $q_{j,k,t}$, that is, the property $k(k = 1,\ldots,l_1)$ of final product j at time period t as a linear function of the flows of its component streams $Q_{i,j,t}$. The quality properties considered linear in this work are: distillation cut-point temperatures (50%, 90%, and 95%, °C), density (20°C, kg/m^3), sulfur content (mg/kg), acidity (mg KOH/(0.1 L)), and cetane number

$$\frac{\sum_{i=1}^{m} a_{i,j,k,t} Q_{i,j,t}}{\sum_{i=1}^{m} Q_{i,j,t}} = q_{j,k,t} \quad j = 1,2,\ldots,n\,; \quad k = 1,2,\ldots,l_1 \tag{6}$$

In fact, $Q_{i,j,t} = Q_{u,s,u',t}$ when $u' \in \mathbf{U}_{p,t}$, and $\sum_{i=1}^{m} Q_{i,j,t} = QP_{j,t} \quad j = 1,2,\ldots,n$.

On the other hand, the flash point (close, °C) is calculated by the nonlinear Eq. 7

$$q_{j,l_1+1,t} = \left[\ln\left(\sum_{i=1}^{m} (0.929^{a_{i,j,l_1+1,t}} \cdot Q_{i,j,t}) \right) - \ln QP_{j,t} \right] \Big/ \ln 0.929 \qquad j=1,2,\ldots,n \tag{7}$$

The kinematic coefficient of viscosity nonlinear property is expressed in Eq. 8

$$q_{j,l_1+2,t} = \exp\left[\sum_{i=1}^{m} \left((Q_{i,j,t}/QP_{j,t}) \cdot \ln a_{i,j,l_1+2,t} \right) \right] \quad j = 1,2,\ldots,n \tag{8}$$

Equation 9 is used to calculate the solidifying point (SP, °C), and was developed as part of this work from the experimental data listed in Table 1.[43] This equation is more complex than the previous ones and was derived through the steps described in detail as follows

$$q_{j,l_1+3,t} = 9.4656T_{j,t}^3 - 57.08217T_{j,t}^2 + 129.075T_{j,t} - 99.2741$$
$$T_{j,t} = f\left[\left(\sum_{i=1}^{m} Q_{i,j,t} \cdot a_{i,j,l_1+3,t} \right) \Big/ QP_{j,t} \right], \quad j = 1,2,\ldots,n; \quad l = l_1 + 3 \tag{9}$$

For each final product j at time t:

Step 1 Assign the numerical values of the conversion factor (T^{i_1}) and solidifying points (SP^{i_1} , $i_1 = 1,2,\ldots,88$) in Table 1 into $T_{j,t}^{i_1}$, $SP_{j,t}^{i_1}$ ($i_1 = 1,2,\ldots,88$; $j = 1,2,\ldots,n$), respectively.

Step 2 Compute the initial value of $SP_{j,t}^0$ through the linear relationship (Eq. 9-1) among final product j and its blending streams i at time t

$$SP_{j,t}^0 = \left(\sum_{i=1}^{m} Q_{i,j,t} \cdot a_{i,j,l_1+3,t} \right) \Big/ QP_{j,t}, \quad j = 1,2,\ldots,n; \quad l = l_1 + 3 \tag{9-1}$$

Step 3 For every $SP_{j,t}^{i_1}$ of each final product j, compute $floor(|SP_{j,t}^0 - SP_{j,t}^{i_1}|*2)$, $(i_1 = 1,2,\ldots,88; j = 1,2,\ldots,n)$. The meaning of the function "*floor*" is as follows: If A is assumed as a float number, then "*floor*(A) " means rounds the value of A to the nearest integer less than or equal to A. If the function value is equal to 0 (zero), record its position i_1. For each final product j, one or two positions can be obtained, then set them to integer variables k_1 and k_2.

If $SP_{j,t}^0$ belongs to an interval ($SP_{j,t}^{k_1}$,$SP_{j,t}^{k_2}$), take $SP_{j,t}^0 = -11.17023$ for example

$$\begin{aligned} &\because floor(|SP_{j,t}^0 - SP_{j,t}^{i_1}|*2) \\ &\quad = floor(|-11.17023 - (-11.5)|*2) = 0, \quad i_1 = 51 \\ &\quad floor(|SP_{j,t}^0 - SP_{j,t}^{i_1+1}|*2) \\ &\quad = floor(|-11.17023 - (-11)|*2) = 0, \quad i_1 + 1 = 52 \end{aligned}$$

$$\therefore k_1 = 51, \quad k_2 = 52$$

If $SP_{j,t}^0$, is on a division point ($SP_{j,t}^{k_1} = SP_{j,t}^{k_2}$) take $SP_{j,t}^0 = -3$, for example

$$\begin{aligned} &\because floor(|SP_{j,t}^0 - SP_{j,t}^{i_1}|*2) \\ &\quad = floor(|-3 - (-3)|*2) = 0, \quad i_1 = 68 \\ &\quad floor(|SP_{j,t}^0 - SP_{j,t}^{i_1+1}|*2) \\ &\quad = floor(|-3 - (-2.5)|*2) = 1 \neq 0, \quad i_1 + 1 = 69 \end{aligned}$$

$$\therefore k_1 = k_2 = 68$$

Table 1. Solidifying Points (SP, °C) and their Conversion Factors

i_1	SP^{i_1}	T^{i_1}	i_1	SP^{i_1}	T^{i_1}	i_1	SP^{i_1}	T^{i_1}	i_1	SP^{i_1}	T^{i_1}
1	−36.5	0.6597	23	−25.5	0.8369	45	−14.5	1.0803	67	−3.5	1.4586
2	−36	0.6695	24	−25	0.8437	46	−14	1.0905	68	−3	1.4818
3	−35.5	0.6793	25	−24.5	0.8508	47	−13.5	1.1001	69	−2.5	1.506
4	−35	0.6889	26	−24	0.8584	48	−13	1.1115	70	−2	1.5282
5	−34.5	0.6982	27	−23.5	0.8665	49	−12.5	1.1228	71	−1.5	1.5514
6	−34	0.7062	28	−23	0.8768	50	−12	1.1356	72	−1	1.5744
7	−33.5	0.7137	29	−22.5	0.8886	51	−11.5	1.1507	73	−0.5	1.5962
8	−33	0.7206	30	−22	0.9011	52	−11	1.1665	74	0	1.6184
9	−32.5	0.7277	31	−21.5	0.914	53	−10.5	1.1828	75	0.5	1.6412
10	−32	0.734	32	−21	0.927	54	−10	1.1995	76	1	1.664
11	−31.5	0.7414	33	−20.5	0.94	55	−9.5	1.2166	77	1.5	1.6897
12	−31	0.7486	34	−20	0.9512	56	−9	1.2324	78	2	1.7176
13	−30.5	0.7559	35	−19.5	0.9621	57	−8.5	1.2481	79	2.5	1.7481
14	−30	0.7632	36	−19	0.9733	58	−8	1.2643	80	3	1.7795
15	−29.5	0.7707	37	−18.5	0.9848	59	−7.5	1.2811	81	3.5	1.8115
16	−29	0.7784	38	−18	0.9955	60	−7	1.2989	82	4	1.844
17	−28.5	0.7868	39	−17.5	1.0074	61	−6.5	1.3185	83	4.5	1.8759
18	−28	0.7954	40	−17	1.02	62	−6	1.3404	84	5	1.9051
19	−27.5	0.8041	41	−16.5	1.0326	63	−5.5	1.3633	85	5.5	1.9345
20	−27	0.8128	42	−16	1.0452	64	−5	1.3868	86	6	1.964
21	−26.5	0.8215	43	−15.5	1.0577	65	−4.5	1.4109	87	6.5	1.995
22	−26	0.83	44	−15	1.07	66	−4	1.4351	88	7	2.0269

Step 4 Compute the value of $T_{j,t}$ using linear interpolation Eq. 9-2 (Figure 2)

$$T_{j,t} = T_{j,t}^{k_1} + \left[\left(T_{j,t}^{k_2} - T_{j,t}^{k_1}\right) * \left(SP_{j,t}^{0} - SP_{j,t}^{k_1}\right)\right] \Big/ \left(SP_{j,t}^{k_2} - SP_{j,t}^{k_1}\right) \tag{9-2}$$

Equation 9-2 can be proved as follows

$$\because \frac{\overline{BC}}{\overline{DE}} = \frac{\overline{AC}}{\overline{AE}} \quad \therefore \overline{BC} = \overline{DE} \cdot \frac{\overline{AC}}{\overline{AE}} = \left(T_{j,t}^{k_2} - T_{j,t}^{k_1}\right) \cdot \left(SP_{j,t}^{0} - SP_{j,t}^{k_1}\right) \Big/ \left(SP_{j,t}^{k_2} - SP_{j,t}^{k_1}\right)$$

$$\therefore T_{j,t} = T_{j,t}^{k_1} + \overline{BC} = T_{j,t}^{k_1} + \left[\left(T_{j,t}^{k_2} - T_{j,t}^{k_1}\right) * \left(SP_{j,t}^{0} - SP_{j,t}^{k_1}\right)\right] \Big/ \left(SP_{j,t}^{k_2} - SP_{j,t}^{k_1}\right)$$

For $SP_{j,t}^{0} = -11.17023$; $k_1 = 51$, $k_2 = 52$; $SP_{j,t}^{k_1} = -11.5$, $SP_{j,t}^{k_2} = -11$; $\Rightarrow T_{j,t} = 1.161121$.

For $SP_{j,t}^{0} = -3$; $k_1 = k_2 = 68$; $SP_{j,t}^{k_1} = SP_{j,t}^{k_2} = -3$; $\Rightarrow T_{j,t} = 1.4818$.

Step 5 Compute the solidifying point nonlinear property $q_{j,I_1+3,t}$ using Eq. 9-3 for final product j at time t

$$q_{j,I_1+3,t} = 9.4656 T_{j,t}^3 - 57.08217 T_{j,t}^2 + 129.075 T_{j,t} - 99.2741 \tag{9-3}$$

For $T_{j,t} = 1.161121 \Rightarrow q_{j,I_1+3,t} = 9.4656T_{j,t}^3 - 57.08217T_{j,t}^2 + 129.075T_{j,t} - 99.2741 = -11.54302$

For $T_{j,t} = 1.4818 \Rightarrow q_{j,I_1+3,t} = 9.4656T_{j,t}^3 - 57.08217T_{j,t}^2 + 129.075T_{j,t} - 99.2741 = -2.5503$

The detailed computing steps we developed are summarized as the flow chart in Figure 3.

Equation 10 means the property of final product j must belong to the scope from minimum to maximum values required by related product criterion at time t

$$b_{\min,j,k,t} \le q_{j,k,t} \le b_{\max,j,k,t} \quad j = 1,2,\ldots,n; \quad k = 1,2,\ldots,l \tag{10}$$

Except for the solidifying point, the values of all the parameters and variables in the model are positive.

Data-driven rolling-horizon optimal control strategy

The general scheduling time horizon of our diesel online scheduling MINLP model is the equivalent discrete time intervals of 1 day. If some events (certain or uncertain events) happen and their beginning or ending time are not restricted to the boundaries of 1 day, the beginning and ending time are used to divide the day into several continuous time intervals. These continuous time intervals and the general discrete time intervals of 1 day are the ‘‘rolling-horizon’’ periods. At each of the rolling-horizon periods, the flow rates and properties of relevant streams must be updated online. After that, the rescheduling processes are driven by these updated data. In this way, we can make decisions for the daily online

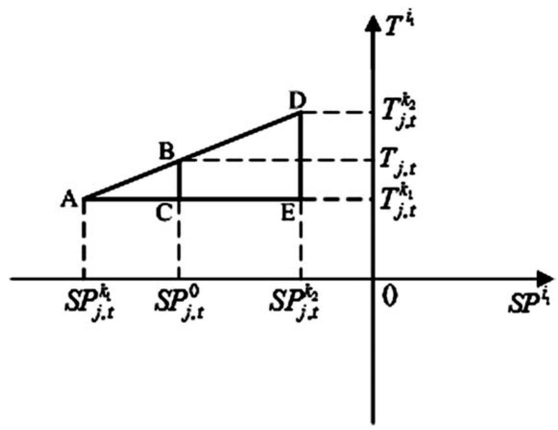

Figure 2. Illustration for the linear interpolation method of Eq. 9-2.

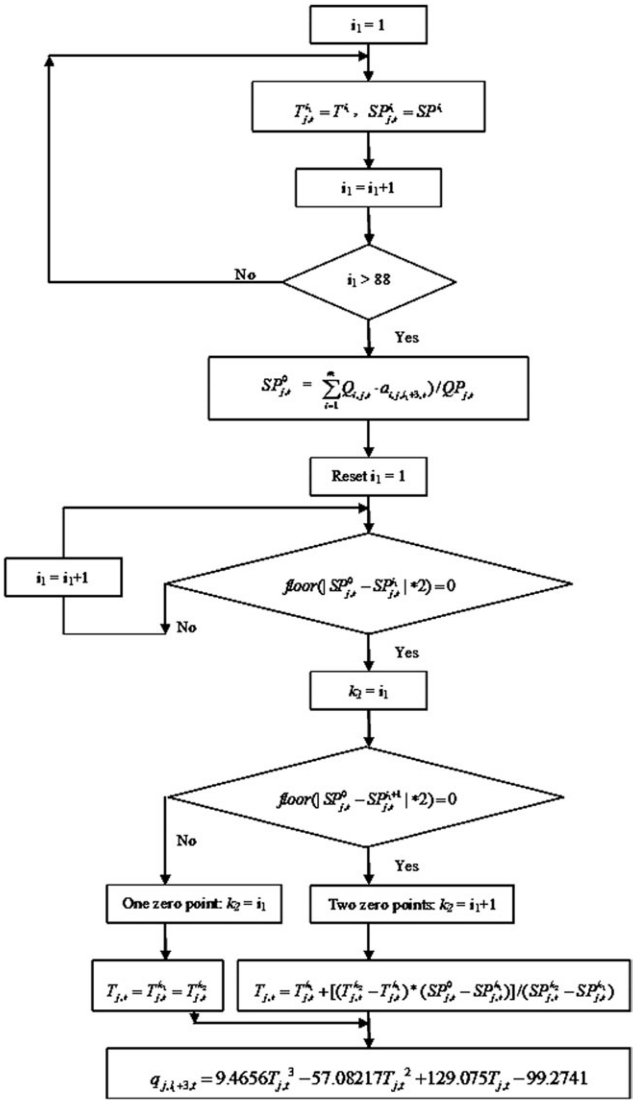

Figure 3. Flow chart for the computing steps of the solidifying point.

scheduling and blending tasks in time. We name this kind of method as data-driven rolling-horizon optimal control strategy. The detailed process is summarized in following steps as well as in Figure 4.

Step 1 Set the discrete time interval of a new day.

Step 2 Check the certain events of this day and previous days for regular production. If some certain events happen, go to Step 3. If there is no event, check the quality fluctuation status for each of the intermediate streams. If the fluctuations exist, go to Step 5; if the answer is no, use the latest schedule and go to Step 7.

Step 3 The beginning time of these certain events of this day and the ending time of previous days are recorded and used to divide this day into several continuous time intervals.

Step 4 Update the flow rates of relevant streams in the scheduling model.

Step 5 Update the qualities of relevant streams in the scheduling model.

Step 6 Use the updated data to drive the rescheduling processes at present time intervals.

Step 7 Check the time. If it is the end of this day, go to Step 1; if it is not, go to Step 8.

Step 8 Check the uncertain events of this day. If some uncertain events happen, go to Step 9; if there is no event, continue the former schedule of this day, and go to Step 13.

Step 9 The beginning time of these uncertain events are recorded and used to divide this time horizon into several new continuous time intervals.

Step 10 Update the flow rates of relevant streams in the scheduling model.

Step 11 Update the qualities of relevant streams in the scheduling model.

Step 12 Use the updated data to drive the rescheduling processes at these updated time intervals.

Step 13 Check the time. If it is the end of this day, go to Step 1; if it is not, go to Step 8.

A Real-world Refinery Application

The background information of the real-world refinery

The real-world refinery possesses two CDUs of different age. The older CDU can only process high-quality crude oils or crude oil blends, which means lower concentration of acid and sulfur, etc., whereas the newer one can process inferior crudes and has larger process ability. The distillate fractions from the two CDUs and the product streams from other units or storage tanks related to diesel production are processed together in succeeding steps.

Besides these two crude oil distillation units and their respective vacuum distillation units (CDU1, CDU2), the refinery also includes two hydrotreating units (2#HT1, 3#HT2), one lube oil hydrotreating unit (LHT), one temporary blending tank (MP) used for storing one of the remaining streams or all the remaining streams at one previous time interval, and two groups of final diesel product blending tanks (DP1–0# Metropolitan Diesel; DP2–0# Regular Diesel). The distillates of splitter 1, 2, 3 from CDU1, the distillates of splitter 1, 2, 3, 6 from CDU2, the diesel distillate from 2#HT1, 3#HT2 and LHT, and the component stored in the temporary blending tank MP ($Q_{10,1}/Q_{10,2}$) are sent directly to DP1 and DP2. The distillates of splitter 4, 5, 6 from CDU1, the distillates of splitter 4, 5, 6 from CDU2, the FCC (fluid catalytic cracking) diesel (Q_{f1}/Q_{f4}) from fluid catalytic cracking units, the coking diesel (Q_{f2}/Q_{f5}) from coking units, and the coking gasoline (Q_{f3}/Q_{f6}) from coking units are mixed first in given proportions, and then are sent to the two hydrotreating units. The schematic representation for diesel production process of the real-world refinery is shown in Figure 5.

The detailed online scheduling model for diesel production of the real-world refinery

The target of this application is to propose the daily scheduling and blending tasks for diesel production of one entire month. The refinery produced two grades of diesels (0# Metropolitan Diesel and 0# Regular Diesel) in that month. The 0# Metropolitan Diesel is the most valuable product. The relevant diesel specifications are given in Table 2.

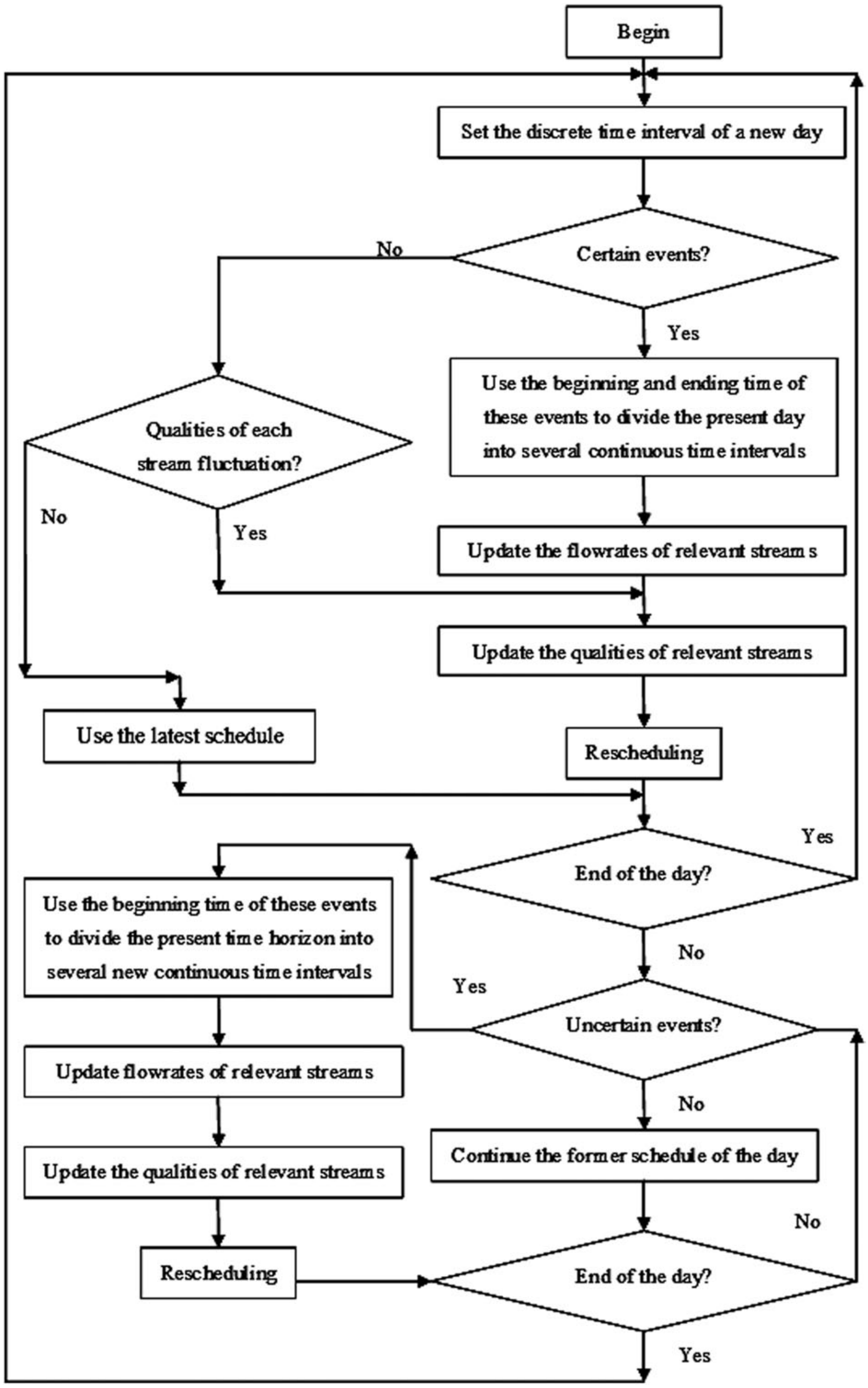

Figure 4. The process of data-driven rolling-horizon control strategy.

The detailed online scheduling model is as follows.

Objective:

$$\text{Max} \quad QP_{1,t} + QP_{2,t}$$

Subject to:

Quantity conservation constraints:

Feed flow rates:

$QF_{CDU1,t}$ and $QF_{CDU2,t}$ are given data.

$$\begin{aligned} QF_{HT1,t} &= Q_{CDU1,s4,HT1,t} + Q_{CDU1,s5,HT1,t} + Q_{CDU1,s6,HT1,t} \\ &\quad + Q_{CDU2,s4,HT1,t} + Q_{CDU2,s5,HT1,t} + Q_{CDU2,s6,HT1,t} \\ &\quad + Q_{f1,t} + Q_{f2,t} + Q_{f3,t}; \\ Q_{f1,01,t} &= Q_{CDU1,S4,HT1,t} + Q_{CDU1,S5,HT1,t} + Q_{CDU1,S6,HT1,t} \\ &\quad + Q_{CDU2,S4,HT1,t} + Q_{CDU2,S5,HT1,t} + Q_{CDU2,S6,HT1,t}; \\ &\quad Q_{f1,t} = 7.356 * Q_{f1,01,t};\ Q_{f2,t} = 3.314 * Q_{f1,01,t}; \\ &\quad Q_{f3,t} = 1.785 * Q_{f1,01,t}; QF_{HT1,t} < 3000. \end{aligned}$$

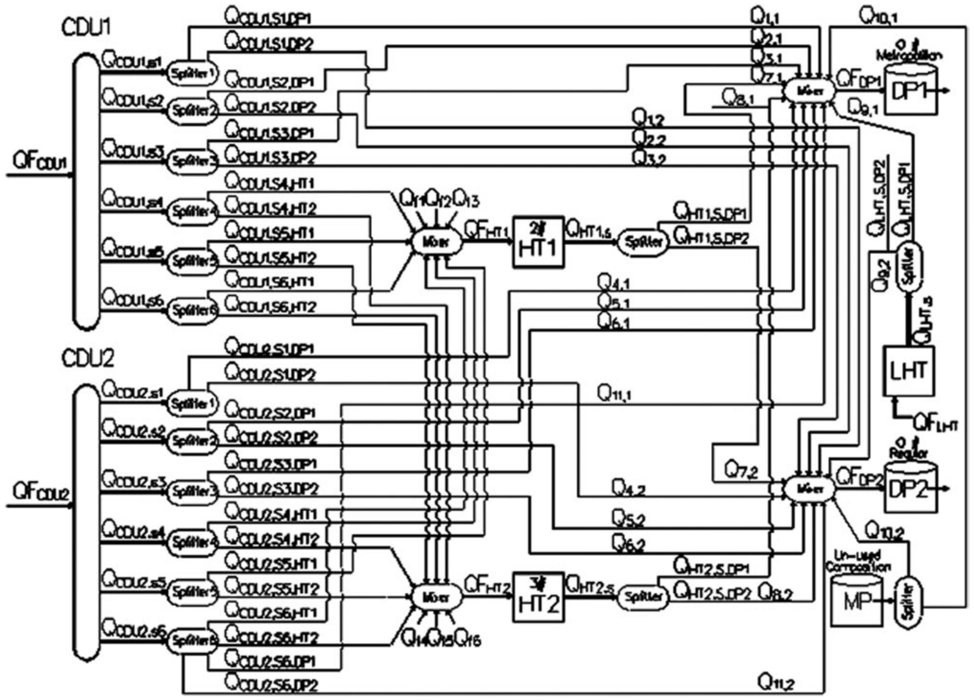

Figure 5. Schematic representation model for diesel production of the real-world refinery.

$$QF_{HT2,t} = Q_{CDU1,s4,HT2,t} + Q_{CDU1,s5,HT2,t} + Q_{CDU1,s6,HT2,t} + Q_{CDU2,s4,HT2,t} + Q_{CDU2,s5,HT2,t} + Q_{CDU2,s6,HT2,t} + Q_{f4,t} + Q_{f5,t} + Q_{f6,t};$$

$$Q_{f1,02,t} = Q_{CDU1,S4,HT2,t} + Q_{CDU1,S5,HT2,t} + Q_{CDU1,S6,HT2,t} + Q_{CDU2,S4,HT2,t} + Q_{CDU2,S5,HT2,t} + Q_{CDU2,S6,HT2,t};$$

$$Q_{f4,t} = 0.704 * Q_{f1,02,t};\ Q_{f5,t} = 0.543 * Q_{f1,02,t};$$

$$Q_{f6,t} = 0.3 * Q_{f1,02,t};\ QF_{HT2,t} < 2400.$$

$$QF_{DP1,t} = Q_{CDU1,s1,DP1,t} + Q_{CDU1,s2,DP1,t} + Q_{CDU1,s3,DP1,t} + Q_{CDU2,s1,DP1,t} + Q_{CDU2,s2,DP1,t} + Q_{CDU2,s3,DP1,t} + Q_{HT1,s,DP1,t} + Q_{HT2,s,DP1,t} + Q_{LHT,s,DP1,t} + Q_{10,1,t} + Q_{CDU2,S6,DP1,t};$$

$$QF_{DP2,t} = Q_{CDU1,s1,DP2,t} + Q_{CDU1,s2,DP2,t} + Q_{CDU1,s3,DP2,t} + Q_{CDU2,s1,DP2,t} + Q_{CDU2,s2,DP2,t} + Q_{CDU2,s3,DP2,t} + Q_{HT1,s,DP2,t} + Q_{HT2,s,DP2,t} + Q_{LHT,s,DP2,t} + Q_{10,2,t} + Q_{CDU2,S6,DP2,t};$$

Table 2. Specifications of Current Diesel Products

Items	$0^{\#}$ Regular	$0^{\#}$ Metropolitan	$-10^{\#}$ Regular
Sulfur Content (mg/kg)	≤2000	≤500	≤2000
Viscosity (20°C, mm^2/s)	3∼8	3∼8	3∼8
Solidifying Point (°C)	≤0	≤0	≤−10
Acidity (mg KOH/(0.1 L))	≤7	≤5	≤7
Density (20°C, kg/m^3)	820∼860	820∼860	820∼860
Flash Point (close) (°C)	≥56	≥55	≥56
Cetane Number	≥45	≥49	≥45
Distillation Cut-point (°C):			
50%	≤298	≤300	≤298
90%	≤353	≤355	≤353
95%	≤363	≤365	≤363

The flow rates of streams generated in relevant units:

$$Q_{CDU1,s1,t} = d_{CDU1,s1,t}\% \cdot QF_{CDU1,t};\ Q_{CDU2,s1,t} = d_{CDU2,s1,t}\% \cdot QF_{CDU2,t};$$

$$Q_{CDU1,s2,t} = d_{CDU1,s2,t}\% \cdot QF_{CDU1,t};\ Q_{CDU2,s2,t} = d_{CDU2,s2,t}\% \cdot QF_{CDU2,t};$$

$$Q_{CDU1,s3,t} = d_{CDU1,s3,t}\% \cdot QF_{CDU1,t};\ Q_{CDU2,s3,t} = d_{CDU2,s3,t}\% \cdot QF_{CDU2,t};$$

$$Q_{CDU1,s4,t} = d_{CDU1,s4,t}\% \cdot QF_{CDU1,t};\ Q_{CDU2,s4,t} = d_{CDU2,s4,t}\% \cdot QF_{CDU2,t};$$

$$Q_{CDU1,s5,t} = d_{CDU1,s5,t}\% \cdot QF_{CDU1,t};\ Q_{CDU2,s5,t} = d_{CDU2,s5,t}\% \cdot QF_{CDU2,t};$$

$$Q_{CDU1,s6,t} = d_{CDU1,s6,t}\% \cdot QF_{CDU1,t};\ Q_{CDU2,s6,t} = d_{CDU2,s6,t}\% \cdot QF_{CDU2,t};$$

$$Q_{HT1,s,t} = d_{HT1,s,t}\% \cdot QF_{HT1,t};\ Q_{HT2,s,t} = d_{HT2,s,t}\% \cdot QF_{HT2,t};\ Q_{LHT,s,t} = d_{LHT,s,t}\% \cdot QF_{LHT,t};$$

$Q_{MP,st}$ is selected and computed online.

The flow rates of streams generated in upstream units equal the sum of their branch streams feeding downstream units:

$$Q_{CDU1,s1,t} \le Q_{CDU1,s1,DP1,t} + Q_{CDU1,s1,DP2,t};\ Q_{CDU1,s1,left,t} = Q_{CDU1,s1,t} - (Q_{CDU1,s1,DP1,t} + Q_{CDU1,s1,DP2,t});$$

$$Q_{CDU1,s2,t} \le Q_{CDU1,s2,DP1,t} + Q_{CDU1,s2,DP2,t};\ Q_{CDU1,s2,left,t} = Q_{CDU1,s2,t} - (Q_{CDU1,s2,DP1,t} + Q_{CDU1,s2,DP2,t});$$

$$Q_{CDU1,s3,t} \le Q_{CDU1,s3,DP1,t} + Q_{CDU1,s3,DP2,t};\ Q_{CDU1,s3,left,t} = Q_{CDU1,s3,t} - (Q_{CDU1,s3,DP1,t} + Q_{CDU1,s3,DP2,t});$$

$$Q_{CDU1,s4,t} \le Q_{CDU1,s4,HT1,t} + Q_{CDU1,s4,HT2,t};\ Q_{CDU1,s4,left,t} = Q_{CDU1,s4,t} - (Q_{CDU1,s4,HT1,t} + Q_{CDU1,s4,HT2,t});$$

$$Q_{CDU1,s5,t} \le Q_{CDU1,s5,HT1,t} + Q_{CDU1,s5,HT2,t};\ Q_{CDU1,s5,left,t} = Q_{CDU1,s5,t} - (Q_{CDU1,s5,HT1,t} + Q_{CDU1,s5,HT2,t});$$

$$Q_{CDU1,s6,t} \le Q_{CDU1,s6,HT1,t} + Q_{CDU1,s6,HT2,t};\ Q_{CDU1,s6,left,t} = Q_{CDU1,s6,t} - (Q_{CDU1,s6,HT1,t} + Q_{CDU1,s6,HT2,t});$$

$$Q_{CDU2,s1,t} \le Q_{CDU2,s1,DP1,t} + Q_{CDU2,s1,DP2,t};\ Q_{CDU2,s1,left,t} = Q_{CDU2,s1,t} - (Q_{CDU2,s1,DP1,t} + Q_{CDU2,s1,DP2,t});$$

$$Q_{CDU2,s2,t} \le Q_{CDU2,s2,DP1,t} + Q_{CDU2,s2,DP2,t};\ Q_{CDU2,s2,left,t} = Q_{CDU2,s2,t} - (Q_{CDU2,s2,DP1,t} + Q_{CDU2,s2,DP2,t});$$

$$Q_{CDU2,s3,t} \le Q_{CDU2,s3,DP1,t} + Q_{CDU2,s3,DP2,t};\ Q_{CDU2,s3,left,t} = Q_{CDU2,s3,t} - (Q_{CDU2,s3,DP1,t} + Q_{CDU2,s3,DP2,t});$$

$$Q_{CDU2,s4,t} \le Q_{CDU2,s4,HT1,t} + Q_{CDU2,s4,HT2,t};\ Q_{CDU2,s4,left,t} = Q_{CDU2,s4,t} - (Q_{CDU2,s4,HT1,t} + Q_{CDU2,s4,HT2,t});$$

$$Q_{CDU2,s5,t} \le Q_{CDU2,s5,HT1,t} + Q_{CDU2,s5,HT2,t};\ Q_{CDU2,s5,left,t} = Q_{CDU2,s5,t} - (Q_{CDU2,s5,HT1,t} + Q_{CDU2,s5,HT2,t});$$

$$Q_{CDU2,s6,t} \le Q_{CDU2,s6,HT1,t} + Q_{CDU2,s6,HT2,t} + Q_{CDU2,s6,DP1,t} + Q_{CDU2,s6,DP2,t};$$

$$Q_{CDU2,s6,left,t} = Q_{CDU2,s6,t} - (Q_{CDU2,s6,HT1,t} + Q_{CDU2,s6,HT2,t} + Q_{CDU2,s6,DP1,t} + Q_{CDU2,s6,DP2,t});$$

$$Q_{HT1,s,t} \le Q_{HT1,s,DP1,t} + Q_{HT1,s,DP2,t};\ Q_{HT1,s,left,t} = Q_{HT1,s,t} - (Q_{HT1,s,DP1,t} + Q_{HT1,s,DP2,t});$$

$$Q_{HT2,s,t} \le Q_{HT2,s,DP1,t} + Q_{HT2,s,DP2,t};\ Q_{HT2,s,left,t} = Q_{HT2,s,t} - (Q_{HT2,s,DP1,t} + Q_{HT2,s,DP2,t});$$

$$Q_{LHT,s,t} \le Q_{LHT,s,DP1,t} + Q_{LHT,s,DP2,t};\ Q_{LHT,s,left,t} = Q_{LHT,s,t} - (Q_{LHT,s,DP1,t} + Q_{LHT,s,DP2,t});$$

$$Q_{MP,s,t} \le Q_{MP,s,DP1,t} + Q_{MP,s,DP2,t};\ Q_{MP,s,left,t} = Q_{MP,s,t} - (Q_{MP,s,DP1,t} + Q_{MP,s,DP2,t}).$$

The following streams are renamed in order to represent their qualities easily:

$$Q_{1,1,t} = Q_{CDU1,s1,DP1,t};\ Q_{1,2,t} = Q_{CDU1,s1,DP2,t};$$

$$Q_{2,1,t} = Q_{CDU1,s2,DP1,t};\ Q_{2,2,t} = Q_{CDU1,s2,DP2,t};$$

$$Q_{3,1,t} = Q_{CDU1,s3,DP1,t};\ Q_{3,2,t} = Q_{CDU1,s3,DP2,t};$$

$$Q_{4,1,t} = Q_{CDU2,s1,DP1,t};\ Q_{4,2,t} = Q_{CDU2,s1,DP2,t};$$

$$Q_{5,1,t} = Q_{CDU2,s2,DP1,t};\ Q_{5,2,t} = Q_{CDU2,s2,DP2,t};$$

$$Q_{6,1,t} = Q_{CDU2,s3,DP1,t};\ Q_{6,2,t} = Q_{CDU2,s3,DP2,t};$$

$$Q_{7,1,t} = Q_{HT1,s,DP1,t};\ Q_{7,2,t} = Q_{HT1,s,DP2,t};$$

$$Q_{8,1,t} = Q_{HT2,s,DP1,t};\ Q_{8,2,t} = Q_{HT2,s,DP2,t};$$

$$Q_{9,1,t} = Q_{LHT,s,DP1,t};\ Q_{9,2,t} = Q_{LHT,s,DP2,t};$$

$$Q_{10,1,t} = Q_{MP,s,DP1,t};\ Q_{10,2,t} = Q_{MP,s,DP2,t};$$

$$Q_{11,1,t} = Q_{CDU2,S6,DP1,t};\ Q_{11,2,t} = Q_{CDU2,S6,DP2,t};$$

$$QP_{1,t} = QF_{DP1,t} = Q_{1,1,t} + Q_{2,1,t} + Q_{3,1,t} + Q_{4,1,t} + Q_{5,1,t} + Q_{6,1,t} + Q_{7,1,t} + Q_{8,1,t} + Q_{9,1,t} + Q_{10,1,t} + Q_{11,1,t};$$

$$QP_{2,t} = QF_{DP2,t} = Q_{1,2,t} + Q_{2,2,t} + Q_{3,2,t} + Q_{4,2,t} + Q_{5,2,t} + Q_{6,2,t} + Q_{7,2,t} + Q_{8,2,t} + Q_{9,2,t} + Q_{10,2,t} + Q_{11,2}.$$

Quality constitutive relations constraints:

Linear quality constraints:

50% Distillation Cut-point (°C):

$$q_{1,1,t} = \frac{\sum_{i=1}^{11} (a_{i,1,1,t} \cdot Q_{i,1,t})}{QP_{1,t}} \le 300;$$

$$q_{2,1,t} = \frac{\sum_{i=1}^{11} (a_{i,2,1,t} \cdot Q_{i,2,t})}{QP_{2,t}} \le 298;$$

90% Distillation Cut-point (°C):

$$q_{1,2,t} = \frac{\sum_{i=1}^{11} (a_{i,1,2,t} \cdot Q_{i,1,t})}{QP_{1,t}} \le 355;$$

$$q_{2,2,t} = \frac{\sum_{i=1}^{11} (a_{i,2,2,t} \cdot Q_{i,2,t})}{QP_{2,t}} \le 353;$$

95% Distillation cut-point (°C):

$$q_{1,3,t} = \frac{\sum_{i=1}^{11} (a_{i,1,3,t} \cdot Q_{i,1,t})}{QP_{1,t}} \le 365;$$

$$q_{2,3,t} = \frac{\sum_{i=1}^{11} (a_{i,2,3,t} \cdot Q_{i,2,t})}{QP_{2,t}} \le 363;$$

Density (20°C, kg/m^3):

$$q_{1,4,t} = \frac{\sum_{i=1}^{11} (a_{i,1,4,t} \cdot Q_{i,1,t})}{QP_{1,t}} \in [0.82, 0.86];$$

$$q_{2,4,t} = \frac{\sum_{i=1}^{11} (a_{i,2,4,t} \cdot Q_{i,2,t})}{QP_{2,t}} \in [0.82, 0.86];$$

Sulfur Content (mg/kg):

$$q_{1,5,t} = \frac{\sum_{i=1}^{11} (a_{i,1,5,t} \cdot Q_{i,1,t})}{QP_{1,t}} \le 500;$$

$$q_{2,5,t} = \frac{\sum_{i=1}^{11} (a_{i,2,5,t} \cdot Q_{i,2,t})}{QP_{2,t}} \le 2000;$$

Acidity (mg KOH/(0.1 L)):

$$q_{1,6,t} = \frac{\sum_{i=1}^{11} (a_{i,1,6,t} \cdot Q_{i,1,t})}{QP_{1,t}} \le 5;$$

$$q_{2,6,t} = \frac{\sum_{i=1}^{11} (a_{i,2,6,t} \cdot Q_{i,2,t})}{QP_{2,t}} \le 7;$$

Cetane Number:

$$q_{1,7,t} = \frac{\sum_{i=1}^{11} (a_{i,1,7,t} \cdot Q_{i,1,t})}{QP_{1,t}} \ge 49;$$

$$q_{2,7,t} = \frac{\sum_{i=1}^{11} (a_{i,2,7,t} \cdot Q_{i,2,t})}{QP_{2,t}} \ge 45;$$

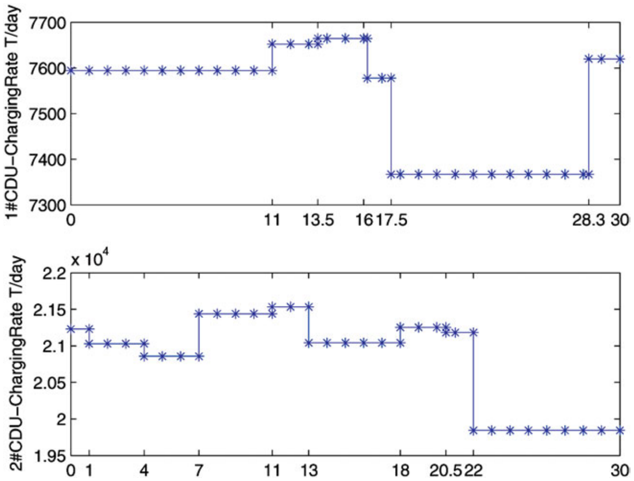

Figure 6. Feed flow rates of crude oils and changeover details of the two CDUs of the entire month.

[Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

Nonlinear quality constraints:
Flash Point (FP) (close, °C):

$$q_{1,8,t} = \frac{\ln \sum_{i=1}^{11} (0.929^{a_{i,1,8,t}} \cdot Q_{i,1,t}) - \ln QP_{1,t}}{\ln 0.929} \geq 55;$$

$$q_{2,8,t} = \frac{\ln \sum_{i=1}^{11} (0.929^{a_{i,2,8,t}} \cdot Q_{i,2,t}) - \ln QP_{2,t}}{\ln 0.929} \geq 56;$$

Viscosity (20°C, mm^2/s):

$$q_{1,9,t} = e^{\frac{\sum_{i=1}^{11} (Q_{i,1,t} \cdot \ln a_{i,1,9,t})}{QP_{1,t}}} \in [3, 8];$$

$$q_{2,9,t} = e^{\frac{\sum_{i=1}^{11} (Q_{i,2,t} \cdot \ln a_{i,2,9,t})}{QP_{2,t}}} \in [3, 8];$$

Solidifying Point (SP) (°C):

$$SP_{1,t}^0 = \frac{\sum_{i=1}^{11} (a_{i,1,11,t} \cdot Q_{i,1,t})}{QP_{1,t}}; \; SP_{2,t}^0 = \frac{\sum_{i=1}^{11} (a_{i,2,11,t} \cdot Q_{i,2,t})}{QP_{2,t}};$$

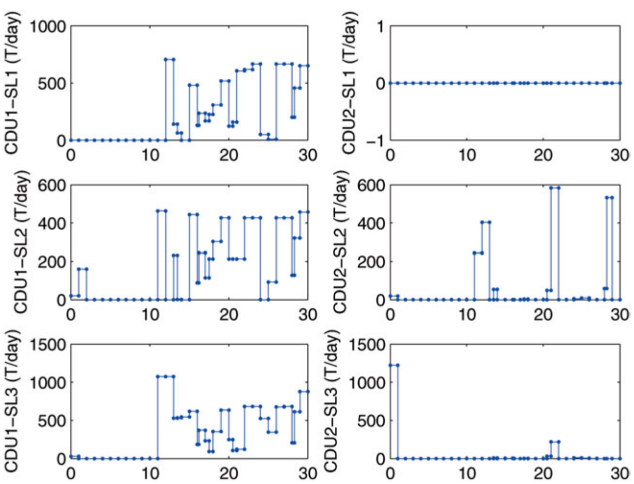

Figure 7. Flow rates of six component streams of 0# Metropolitan Diesel Oil of the entire month (1).

[Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

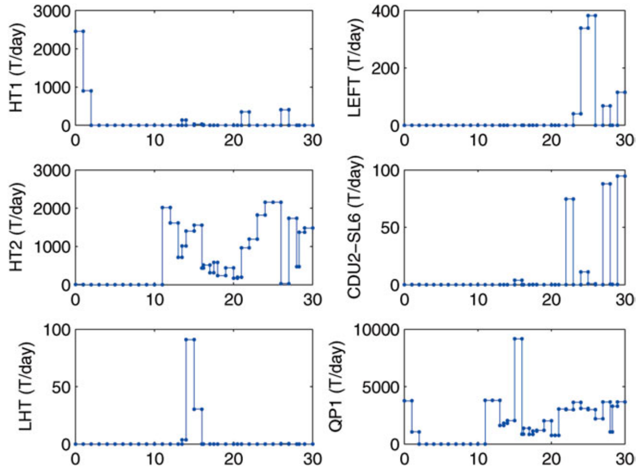

Figure 8. Flow rates of five component streams and final product of 0# Metropolitan Diesel Oil of the entire month (2).

[Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

Compute the value of T_1, T_2 according to the Step 3 of Eq. 9.

$$q_{1,10,t} = 9.4656T_1^3 - 57.08217T_1^2 + 129.075T_1 - 99.2741 \leq 0;$$

$$q_{2,10,t} = 9.4656T_2^3 - 57.08217T_2^2 + 129.075T_2 - 99.2741 \leq 0.$$

The data-driven rolling-horizon control strategy for the real-world refinery

Six types of crude oils or mixed crude oils were processed by CDU1 and nine types by CDU2 in that month. The crude oil feed flow rates of CDU1 and CDU2 of the entire month are concluded in Figure 6. The certain events in that month were the changeovers of crude oils of the two CDUs. Their changeover time must be considered simultaneously. The uncertain events in that month were the rush orders of other products which caused the flow rates of some diesel product streams to zeros.

According to the detailed steps summarized in Figure 4, the daily scheduling time partition of the entire month are as follows (day): 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, **13.5**, 14, 15, 16, **16.2**, 17, **17.5**, 18, 19, 20, **20.5**, 21, 22, 23, 24, 25, 26, 27, 28, **28.3**, 29, 30. There have been 35 rolling-horizon discrete and continuous time intervals, and the online scheduling model updated with the latest data is driven and computed at each of the time intervals.

The detailed optimal results

Computing results of the entire month:

There are 35 rolling-horizon time intervals in the month. The 35 groups' flow rates of 11 components and 2 products are shown in Figure 7∼Figure 10. Figure 7 and Figure 8 show the flow rates of 11 component streams and the final product of 0# Metropolitan Diesel Oil of the entire month. Figures 9 and 10 show the flow rates of 11 component streams, and the final product of 0# regular diesel oil of the entire month. The unit of flow rate is T/day, T = 1,000 kg.

The quantities of the remaining streams stored in four intermediate tanks and the status of the temporary blending tank (MP) are shown in Table 3. The remaining streams

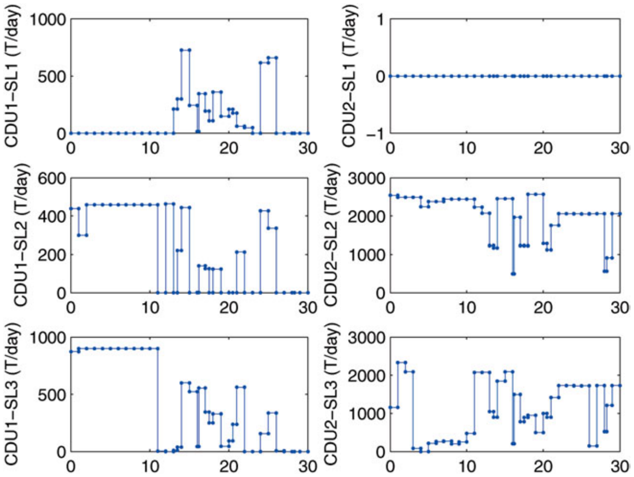

Figure 9. Flow rates of six component streams of 0# Regular Diesel Oil of the entire month (1).

[Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

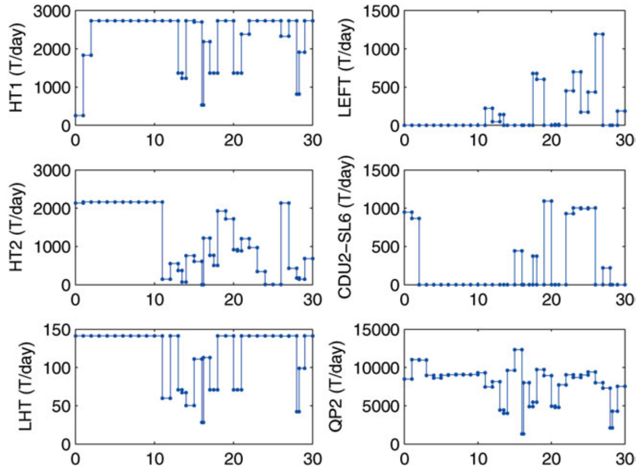

Figure 10. Flow rates of five component streams and final product of 0# Regular Diesel Oil of the entire month (2).

[Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

(boldface data) are sent first to several temporary intermediate tanks (①, ②, ③, ④). Then they go to the MP tank when necessary. The changeover and transfer time among ①, ②, ③, ④ and the MP tank are assumed to zero. Some representations of the status of MP are as follows:

"(3)-$Q_{CDU2\text{-}S3}$-222.0754→①" – 222.0754 T of the remaining stream S3 generated in CDU2 of the 3rd day are sent to the temporary intermediate tank ① at this time interval.

"(3)-$Q_{CDU2\text{-}S6}$-864.3185→817.6141②MP" – 864.3185 T of the remaining stream S6 generated in CDU2 of the 3rd

Table 3. Status of the Remaining Streams in Intermediate Tanks and MP of the Entire Month (Unit: T = 1,000 kg)

day	$Q_{CDU1\text{-}S4}$	$Q_{CDU2\text{-}S3}$	$Q_{CDU2\text{-}S5}$	$Q_{CDU2\text{-}S6}$	MP-status
1	0	0	0	0	
2	0	0	0	0	
3	0	**222.0754**	0	**864.3185**	(3)-$Q_{CDU2\text{-}S3}$-222.0754→①; (3)-$Q_{CDU2\text{-}S6}$-864.3185→②
4	0	2251.895	0	864.3185	
5	0	2083.647	0	849.9543	
6	0	1869.024	0	849.9543	
7	0	1822.790	0	849.9543	
8	0	1937.073	0	933.9889	
9	0	2206.202	0	862.7716	
10	0	1956.013	0	933.9889	
11	0	1733.490	0	933.9889	
12	0	0	26.52266	1119.742	(3)-$Q_{CDU2\text{-}S3}$-222.0754→0①MP
13	0	0	26.52266	1119.742	(3)-$Q_{CDU2\text{-}S6}$-864.3185→817.6141②MP
13-13.5	**58.54086**	0	**44.18904**	**458.4425**	(3)- $Q_{CDU2\text{-}S6}$-817.6141→677.0800②MP; (13-13.5)-$Q_{CDU2\text{-}S5}$+$Q_{CDU2\text{-}S6}$+$Q_{CDU1\text{-}S4}$-561.1724→①
13.5-14	86.99559	142.1270	14.25451	498.7049	
15	**173.9912**	246.8971	**88.37808**	**937.5407**	(15)- $Q_{CDU2\text{-}S5}$+$Q_{CDU2\text{-}S6}$+$Q_{CDU1\text{-}S4}$-1199.91→③
16	114.1221	0	88.37808	551.1886	
16-16.2	**34.79824**	235.6244	**17.67562**	**187.5081**	(16-16.2-17)- $Q_{CDU2\text{-}S5}$+$Q_{CDU2\text{-}S6}$+$Q_{CDU1\text{-}S4}$-1192.2437→④
16.2-17	**145.4916**	180.0869	**70.70246**	**736.0677**	
17-17.5	90.93228	269.7213	16.11337	488.1180	
17.5-18	124.4908	153.0511	27.98057	124.2271	(3)-$Q_{CDU2\text{-}S6}$-677.0800→0②MP
19	215.8543	1115.807	20.18835	1092.394	(13-13.5)- $Q_{CDU2\text{-}S5}$+$Q_{CDU2\text{-}S6}$+$Q_{CDU1\text{-}S4}$-561.1724→0①MP
20	215.8543	1571.735	20.18835	0	
20-20.5	107.9271	36.11778	10.09417	546.1970	
20.5-21	107.9271	0	32.83314	543.9046	(15)- $Q_{CDU2\text{-}S5}$+$Q_{CDU2\text{-}S6}$+$Q_{CDU1\text{-}S4}$-1199.91→1188.626③MP
22	**215.8543**	**231.0870**	**65.66628**	**1087.809**	(22)- $Q_{CDU2\text{-}S5}$+$Q_{CDU2\text{-}S6}$+$Q_{CDU1\text{-}S4}$-1369.32958→①
23	215.8543	0	23.54132	0	(15)- $Q_{CDU2\text{-}S5}$+$Q_{CDU2\text{-}S6}$+$Q_{CDU1\text{-}S4}$-1188.626→737.0923③MP
24	215.8543	0	23.54132	0	(15)- $Q_{CDU2\text{-}S5}$+$Q_{CDU2\text{-}S6}$+$Q_{CDU1\text{-}S4}$-737.0923→0③MP
25	215.8543	0	23.54132	0	(22)-$Q_{CDU2\text{-}S5}$+$Q_{CDU2\text{-}S6}$+$Q_{CDU1\text{-}S4}$-1369.3296→858.4120①MP
26	215.8543	0	23.54132	0	(22)- $Q_{CDU2\text{-}S5}$+$Q_{CDU2\text{-}S6}$+$Q_{CDU1\text{-}S4}$-858.4120→0①MP
27	215.8543	**1582.177**	23.54132	1002.084	(16-16.2-17)-$Q_{CDU2\text{-}S5}$+$Q_{CDU2\text{-}S6}$+$Q_{CDU1\text{-}S4}$-1192.2437→0④MP
28	215.8543	0	23.54132	696.8730	(27)-$Q_{CDU2\text{-}S3}$-1582.177→1514.685③MP
28-28.3	64.75628	0	7.062397	300.3104	
28.3-29	163.2204	0	40.28180	698.6441	
30	233.1720	0	53.54483	907.5105	(27)-$Q_{CDU2\text{-}S3}$-1514.685→1213.652③MP
∑	3449.0543	21846.6410	811.8243	21040.2464	
Remaining	2820.3781	19811.3016	525.2128	16768.5599	1213.652

Table 4. Optimal Results of the Final

0# Metropolitan		0# Regular	
Optimal component flowrates (T/day)		Optimal component flowrates (T/day)	
$Q_{1,1}$	208.7850	$Q_{1,2}$	458.6689
$Q_{2,1}$	0.000000	$Q_{2,2}$	425.8149
$Q_{3,1}$	290.2752	$Q_{3,2}$	391.1760
$Q_{4,1}$	0.000000	$Q_{4,2}$	0.000000
$Q_{5,1}$	0.000000	$Q_{5,2}$	2057.745
$Q_{6,1}$	0.000000	$Q_{6,2}$	1728.347
$Q_{7,1}$	0.000000	$Q_{7,2}$	2730.000
$Q_{8,1}$	214.1711	$Q_{8,2}$	1945.829
$Q_{9,1}$	0.000000	$Q_{9,2}$	141.2300
$Q_{10,1}$	0.000000	$Q_{10,2}$	0.000000
$Q_{11,1}$	0.176459	$Q_{11,2}$	127.0737
Quality data		Quality data	
50% Distillation Cut-point (°C)	263.8072	50% Distillation Cut-point (°C)	276.7497
90% Distillation Cut-point (°C)	300.6862	90% Distillation Cut-point (°C)	317.1510
95% Distillation Cut-point (°C)	365.0000	95% Distillation Cut-point (°C)	330.7443
Density (20°C, kg/m^3)	834.6413	Density (20°C, kg/m^3)	830.8108
Sulfur Content (mg/kg)	490.0000	Sulfur Content (mg/kg)	1191.473
Acidity (mg KOH/(0.1 L))	4.900000	Acidity (mg KOH/(0.1 L))	4.214188
Cetane Number	51.92794	Cetane Number	45.00000
Flash Point (close) (°C)	55.00000	Flash Point (close) (°C)	64.35098
Viscosity (20°C, mm^2/s)	6.586779	Viscosity (20°C, mm^2/s)	5.475931
SP (°C)	-15.41431	SP(°C)	-11.54302
QP_1 Yield (T)		QP_2 Yield (T)	
713.4067		10005.88	
Total diesel yield of the day:		QP_1+QP_2 = 10719.29	

day are stored in the temporary intermediate tank②. They are transferred to MP at this time interval, and the quantities are 817.6141 T at the end of the interval.

"(22)-$Q_{CDU2\text{-}S5}$+$Q_{CDU2\text{-}S6}$+$Q_{CDU1\text{-}S4}$-1369.32958→858.4120 ①MP" – 1369.32958 T of the remaining streams S5 from CDU2 + S6 from CDU2 + S4 from CDU1 of the 22nd day are stored in the temporary intermediate tank①. They are sent to MP at this time interval, and the quantities are 858.4120 T at the end of the interval.

The detailed input data and calculation results of the 24th day in the month are taken as an example to explain the computing results. The online scheduling model was written in LINGO language in Supplementary Material. A rush order of producing aviation kerosene came that day, and the distillate of splitter 1 from CDU2 was taken away, which caused the flow rate of this stream to zero.

The optimal flow rates and qualities for 11 components and 2 products of the 24th day are shown in Table 4. Figure 11 is the solver status in LINGO 11.0. The Branch and Bound (B-and-B) algorithm of its MINLP Solver was used to solve the scheduling model. The real-world model of the 24th day contains 429 linear variables, 202 nonlinear variables, 176 integer variables, 439 linear constraints, 198 nonlinear constraints. The maximum objective (= $QP_1 + QP_2$) is $1.071\,929 \times 10^4$ T. The runtime of this calculation is 119 s.

Analysis of the optimal results for the whole month:

1. Under the situation of the full-load production of the refinery, the main benefits of our online data-driven rolling-horizon optimal method come from producing more high-valuable diesel (0# Metropolitan diesel), not from increasing the total diesel yields.

2. As shown in Table 3, 4 inferior remaining streams have been stored in 4 intermediate tanks. The distillate of splitter 3 from CDU2 is inferior component with high concentration of sulfur and acid, it has been left $1.981\,130 \times 10^4$ T. The distillates of splitter 5 and 6 from CDU2 have the similar qualities as the splitter 3. The splitter 5 has unused stream 525.2128 T, and the splitter 6 has $1.676\,856 \times 10^4$ T. The distillate of splitter 4 from CDU1 has been left 2820.3781 T. The temporary blending tank (MP) has 1213.652 T unused content.

All these unused streams need to be put to use in later production when better crude oils come. It is a tough task because better crude oils are rare, and the remaining streams usually occupy these storage tanks for a long time. The suggestion of increasing the output of superior blending

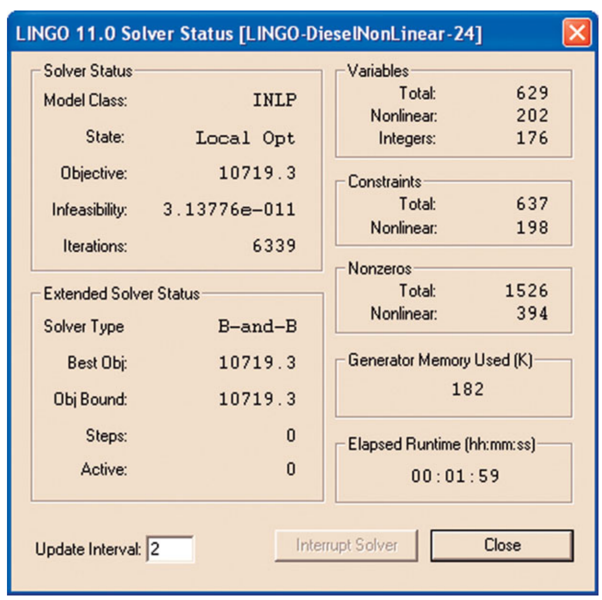

Figure 11. Solver status of the 24th day in LINGO 11.

[Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

components from hydrotreating units has been put forward to the refinery by us.

3. Since the general scheduling horizon is 1 day, the dimension of the data-driven rolling-horizon online model can be accepted in real industry and many kinds of existing software can be used to solve the model.

4. The computing time for once calculation is less than 120 s in our test data.

Conclusions

The diesel scheduling problem addressed in this article is a very complex and highly constrained problem with the characteristics of discrete events and continuous events coexistence, multistage, multiproduct, nonlinear, uncertainty and large scale.

In this investigation, a data-driven rolling-horizon control scheme was developed to find the online optimal scheduling operation strategy for diesel production of a real-world refinery. A general MINLP model has been formulated based on quantity conservation principles and quality constitutive relations. The data variations that drove the MINLP model came from different sources of certain and uncertain events. The scheduling time horizon was divided into fixed discrete time periods which described the regular production and continuous time periods for expected and unexpected events that occurred inside the boundaries of the fixed intervals. This rolling optimal control strategy ensures that the size of the diesel scheduling model can be accepted for industrial online use. These data-driven rolling-horizon approach was applied to a real refinery case study which contains 429 linear variables, 202 nonlinear variables, 176 integer variables, 439 linear constraints and 198 nonlinear constraints, and the problem was effectively solved for a month long time horizon that was decomposed into 35 time periods.

Acknowledgments

The authors thank the anonymous reviewers for their valuable comments and suggestions which greatly improved the contents of this article. Financial support from the National High Technology Research and Development Program of China (No. 2009AA04Z141, 2011AA05A20401), Fundamental Research Funds for the Central Universities, the National Natural Science Foundation of China (No.61174040, 21106039, U1162110), and Shanghai commission of Nature Science (No. 10ZR1408300, 12ZR1408100) is also grateful appreciated.

Notation

Subscripts

u, u' = the names of processing units related to diesel production
s = the name of stream generated in processing unit
j = final product, n is the number of types of diesel final products, such as 0# Metropolitan Diesel, 0# Regular Diesel, −10# Regular Diesel, etc.
i = component i ($i = 1,2,\ldots,m$) participating in blending final product j, m is the number of components participating in final blending
l = number of total product properties considered in final product
l_1 = number of linear properties considered in final product
k = final product property
t = time intervals, it can be an equivalent discrete integer value (1 day) which represent the regular production, or a continuous float value which describe uncertain parameters or occurrence of unexpected events happen

Superscripts

i_1 = division points of solidifying point ($i_1 = 1,2,\ldots,88$) in Table 1

Sets

$\mathbf{U}_{u,t}$ = set of units whose destination is u at time t
$\mathbf{S}_{u',u,t}$ = set of streams leaving units u' and reaching u at time t
$\mathbf{S}_{u,t}$ = set of streams generated in unit u at time t
$\mathbf{U}_{s,u,t}$ = set of units fed from the stream s produced in unit u at time t
$\mathbf{U}_{p,t}$ = set of units whose destination is final products at time t, include those storage tanks for unused remaining streams

Parameters

$QF_{u,t}$ = feed flow rate of unit u at time t
$QF_{u\text{-max}}$ = maximum feed flow rate capacity of unit u
$D_{u,s,t}$ = yield level (%) of stream s generated in unit u at time t
$a_{i,j,k,t}$ = property k of component i of final product j at time t, $k(k = 1, 2, \ldots, l_1, l_1 + 1, \ldots, l)$, l_1 is the number of linear properties considered in final product blending. These property data can be got online from the LAN of a refinery
T^{i_1} = conversion factor in Table 1 at point i_1(=1,2,…,88) when solidifying point (SP) is computed
SP^{i_1} = experimental values of SP in Table 1 at point i_1(=1,2,…,88)
$T^{i_1}_{j,t}$ = SP conversion factor at point i_1(=1,2,…,88) of final product $j(j = 1,2,\ldots,n)$at time t
$SP^{0}_{j,t}$ = initial SP value of final product at time t, computed from Eq. 9-1
$SP^{i_1}_{j,t}$ = experimental values of SP at point $j(j = 1,2,\ldots,88)$ of final product at time t
$b_{\max,j,k,t}$ = maximum values of property k for final product at time t
$b_{\min,j,k,t}$ = minimum values of property k for final product at time t

Variables

$Q_{u,s,t}$ = flow rate of stream s generated in unit u at time t
$Q_{u,s,left,t}$ = flow rate of the remaining stream s generated in unit u at time t
$Q_{u',s,u,t}$ = flow rate of stream s leaving units $u'(\in \mathbf{U}_{u,t})$ and reaching unit u at time t
$Q_{u,s,u',t}$ = flow rate of stream s leaving the unit u and reaching units $u'(\in \mathbf{U}_{s,u,t})$ at time t
$Q_{i,j,t}$ = flow rate of component stream $i(i = 1,2,\ldots,m)$ participating in blending final product j($j = 1,2,\ldots,n$) at time t. In fact $Q_{i,j,t} = Q_{u,s,u',t}$ when $u'(\in \mathbf{U}_{p,t})$ and this description is used for the reason of convenient in computer programming
$QP_{j,t}$ = flow rate of final product $j(j = 1,2,\ldots,n)$ at time t
$q_{j,k,t}$ = property $k(k = 1,2,\ldots,l_1,\ l_1 + 1,\ldots,l)$ of final product at time t, is number of linear properties considered in the final product blending
$T_{j,t}$ = SP conversion factor of final product $j(j = 1,2,\ldots,n)$ at time t
k_1, k_2 = integer variables which record the two closest positions to the initial SP value of each final product j in Table 1

Literature Cited

1. Li J, Karimi IA, Srinivasan R. Recipe determination and scheduling of gasoline blending operations. *AIChE J*. 2010;56:441–465.
2. Mendez CA, Grossmann IE, Harjunkoski I, Kabore P. A simultaneous optimization approach for off-line blending and scheduling of oil-refinery operations. *Comput Chem Eng*. 2006;30:614–634.
3. Pinto JM, Joly M, Moro LFL. Planning and scheduling models for refinery operations. *Comput Chem Eng*. 2000;24:2259–2276.
4. Shah N. Mathematical programming technique for crude oil scheduling. *Comput Chem Eng*. 1996;20:S1227–S1232.
5. Lee H, Pinto JM, Grossmann IE, Park S. Mixed integer linear programming model for refinery short-term scheduling of crude oil unloading with inventory management. *Ind Eng Chem Res*. 1996; 35:1630–1641.
6. Moro LFL, Zanin AC, Pinto JM. A planning model for refinery diesel production. *Comput Chem Eng*. 1998;22:S1039–S1042.
7. Glismann K, Gruhn G. Short-term scheduling and recipe optimization of blending processes. *Comput Chem Eng*. 2001;25: 627–634.
8. Jia Z, Ierapetritou MG, Kelly JD. Refinery short-term scheduling using continuous time formation: crude oil operations. *Ind Eng Chem Res*. 2003;42:3085–3097.

9. Floudas CA, Lin X. Continuous-time versus discrete-time approaches for scheduling of chemical processes: a review. *Comput Chem Eng*. 2004;28:2109–2129.
10. Li Z, Ierapetritou MG. Process scheduling under uncertainty using multiparametric programming. *AIChE J*. 2007;53:3183–3203.
11. Li Z, Ierapetritou MG. Reactive scheduling using parametric programming. *AIChE J*. 2008;54:2610–2623.
12. Sahinidis NV. Optimization under uncertainty: state-of-the-art and opportunities. *Comput Chem Eng*. 2004;28:971–983.
13. Liu ML, Sahinidis NV. Optimization in process planning under uncertainty. *Ind Eng Chem Res*. 1996;35:4154–4165.
14. Charnes A, Cooper WW. Chance-constrained programming. *Manage Sci*. 1959;6:73–79.
15. Gendreau M, Laporte G, Seguin R. Stochastic vehicle routing. *Euro J Oper Res*. 1999;88:3–12.
16. Zhou J, Liu B. New stochastic models for capacitated location-allocation problem. *Comput Ind Eng*. 2003;45:111–125.
17. Cao C, Gu X, Xin Z. Stochastic chance constrained mixed-integer nonlinear programming models and the solution approaches for refinery short-term crude oil scheduling problem, *Appl Math Model*. 2010;34:3231–3243.
18. Vicente RR, Sergio FH, Urmila MD, Salvador HC. Water networks sevurity: A two-stage mixed-integer stochastic program for sensor placement under uncertainty. *Comput Chem Eng*. 2007;31:565–573.
19. Daruppiah R, Grossmann IE. Global optimization of multiscenario mixed integer nonlinear programming models arising in the synthesis of integrated water networks under uncertainty. *Comput Chem Eng*. 2008;32:145–160.
20. Choi SH, Ko JW, Manousiouthakis V. A stochastic approach to global optimization of chemical processes. *Comput Chem Eng*. 1999;23:1351–1356.
21. Pistilopoulos EN, Ierapetritou MG. Novel approach for optimal process design under uncertainty. *Comput Chem Eng*. 1994;19:1089–1110.
22. Shastri Y, Diwekar U. An efficient algorithm for large scale stochastic nonlinear programming problems. *Comput Chem Eng*. 2006;30: 864–877.
23. Jochen T, Guido S, Maren U, Sebastian E. A hybrid evolutionary algorithm for solving two-stage stochastic integer programs in chemical batch scheduling. *Comput Chem Eng*. 2007;31:630–647.
24. Sand G, Engell S. Modeling and solving real-time scheduling problems by stochastic integer programming. *Comput Chem Eng*. 2004; 28:1087–1103.
25. Ahmed S, King A, Parija GA. A multi-stage stochastic integer programming approach for capacity expansion under uncertainty. *J Globa Optim*. 2003;26:3–24.
26. Liu ML, Sahinidis NV. Process planning in a fuzzy environment. *Euro J Oper Res*. 1997b;100:142–169.
27. Zimmermann HJ. *Fuzzy set theory and its application*. Boston: Kluwer Academic Publishers; 1991.
28. Liu BD, Iwamura K. Chance constrained programming with fuzzy parameters. *Fuzzy Sets Syst*. 1998;94:227–237.
29. Cao C, Gu X, Xin Z. Chance constrained programming models for refinery short-term crude oil scheduling problem. *Appl Math Model*. 2009;33:1696–1707.
30. Vin JP, Ierapetritou MG. Robust short-term scheduling of multiproduct batch plants under demand uncertainty. *Ind Eng Chem Res*. 2001;40:4543–4554.
31. Lin X, Janak SL, Floudas CA. A new robust optimization approach for scheduling under uncertainty: I. Bounded uncertainty. *Comput Chem Eng*. 2004;28:1069–1085.
32. Janak SL, Lin X, Floudas CA. A new robust optimization approach for scheduling under uncertainty: II. Uncertainty with known probability distribution. *Comput Chem Eng*. 2007;31:171–195.
33. Jia Z, Ierapetritou MG. Generate pareto optimal solutions of scheduling problems using normal boundary intersection technique. *Comput Chem Eng*. 2007;31:266–280.
34. Jia Z, Ierapetritou MG. Short-term scheduling under uncertainty using MILP sensitivity analysis. *Ind Eng Chem Res*. 2004;43:3782–3791.
35. Rodrigues MTM, Gimeno L, Passos CAS, Campos MD. Reactive scheduling approach for multipurpose chemical batch plants. *Comput Chem Eng*. 1996;20:S1215–1220.
36. Sanmarti E, Huercio A, Espuna A, Puigjaner L. Combined scheduling/reactive scheduling strategy to minimize the effect of process operations uncertainty in batch plants. *Comput Chem Eng*. 1996;20:1263–1268.
37. Honkomp SJ, Mockus L, Reklaitis GV. A framework for schedule evaluation with processing uncertainty. *Comput Chem Eng*. 1999;23: 595–609.
38. Vin JP, Ierapetritou MG. A new approach for efficient rescheduling of multiproduct batch plants. *Ind Eng Chem Res*. 2000;39:4228–4238.
39. Diego R, Jordi C, José MN, Antonio E, Luis P. On-line fault diagnosis system support for reactive scheduling in multipurpose batch chemical plants. *Comput Chem Eng*. 2001;25:829–837.
40. Méndez CA, Cerdá J. An MILP framework for batch reactive scheduling with limited discrete resources. *Comput Chem Eng*. 2004;28: 1059–1068.
41. Janak SL, Floudas CA. Production scheduling of a large-scale industrial batch plant. II. Reactive scheduling. *Ind Eng Chem Res*. 2006; 45:8253–8269.
42. Li F. Multi-Objective Decision Processes under Uncertainty: Applications, Problem Formulations, and Solution Strategies [PhD Thesis]. Carnegie Mellon University, Carnegie Institute of Technology; 2003.
43. Hou X. *China Oil Refining Technology*. Beijing, PR China: China Petrochemical Press; 2001. (in Chinese).

Manuscript received Aug. 25, 2011, and revision received July 16, 2012.