A Two-stage Discriminating Framework for Making Supply Chain Operation Decisions under Uncertainties

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This paper addresses the problem of making supply chain operation decisions for refineries under two types of uncertainties: demand uncertainty and incomplete information shared with suppliers and transport companies. Most of the literature only focus on one uncertainty or treat more uncertainties identically. However, we note that refineries have more power to control uncertainties in procurement and transportation than in demand in the real world. Thus, a two-stage framework for dealing with the considered problem is proposed, which discriminates the two types of uncertainties for decision-making. This framework introduces a new and complete workflow to decision makers. The trade-off between economy and expected value of customer satisfaction level (CSL) under uncertainties is realized by managing the safety stock levels. At the first stage, a new simulation-based optimization approach is introduced to cope with demand uncertainty, where an outer loop for large adjustment and an inner loop for tiny adjustment are integrated. Incomplete information will be revealed gradually and overcome by negotiation loops in the second stage. The target CSL can be achieved or approached when executing the final decisions under considered uncertainties. In addition, a combination of hierarchical supply-chain optimization models and if-then rules based simulator are described for this framework. The performances of this two-stage framework are proved by the case studies.

Key words:
Supply chain, simulation based optimization, uncertainty, customer satisfaction level, safety stock level

1. Introduction

Supply chain (SC) management of the chemical process industry involves two main problems: supply chain design[1] and operation. The latter will be the focus of this paper. SC operation includes quarterly or monthly long-term decisions on procurement, distribution and sales, as well as weekly or even daily dynamic short-term inventory and transportation arrangements. It faces various uncertainties such as demands for products, unit prices of raw materials and products, lead times of deliveries, process failures, and quality failures.[2] Due to inevitable uncertainties, enterprises usually pay more attention to feasibility and robustness rather than global optimum in making decisions on SC operations. This paper addresses the problem of making robust decisions on supply chain operations under the following two main uncertainties: demand uncertainty and incomplete information.

Demand uncertainty may occur frequently and have dominant impact on profits and customer satisfaction. Failure to incorporate a stochastic description of the demand could lead to either unsatisfied customer demand or excessively high inventory holding costs. At the same time, short-term supply chain operation decision making may also suffer from uncertainty due to incomplete information shared with suppliers and transport companies. Facing various refineries, these independent business entities also try to develop optimum sales strategies. Therefore, a refinery cannot gain full information from them unless it makes specific orders including quantity and transaction time details.

In process systems engineering, the optimization problem associated with supply chain management, production planning and scheduling under uncertainty has attracted increasing attention in recent decades. Stochastic programming and simulation-based optimization are two widely used methodologies. Due to the presence of both deterministic and uncertain constraints, the objective function of the stochastic programming always consists of two parts: the deterministic *design* part and the *expected* stochastic *recourse* part. According to the representation of uncertainty, stochastic programming can be categorized into two primary ap-

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proaches, referred to as the continuous probabilistic approach[3,4,5] and scenario-based approach.[1] To avoid introducing nonlinearities into the problem through multivariate integration over the continuous probability space, the probability density function of uncertainties should be easily calculated in the probabilistic approach to translate the stochastic problem into an equivalent deterministic optimization problem and decrease problem size, which limits its scope of use. The scenario-based approach attempts to capture uncertainty by a number of discrete, distinct scenarios and to find robust solutions that perform well under all scenarios. The main disadvantage of this technique is the burden of exponential increase in the problem size accompanying the growth of scenarios.[3] The simulation-based optimization or so-called simulation-optimization strategy is also a popular method. Many simulation-based optimization approaches are used to obtain ideal values of some key parameters.[6−9] Among these approaches, some use optimization in the procedure of evaluating decision making under given values of parameters,[6] others use optimization in the procedure of generating and updating the values of parameters.[7−9] In addition, some simulation-based optimization approaches are used to make a sequence of robust decisions.[10] Reviews of theory and practice developments on simulation-based optimization research have been well investigated.[11]

All the literature listed above deal with only one kind of uncertainty or different uncertainties in the same manner. However, a refinery has more power to manage and control uncertain risks in the real world when facing suppliers and transport companies as part A than facing customers as part B. A refinery has to make every effort to satisfy the customers from the perspective of keeping custom royalty even though their demands may fluctuate abruptly. In contrast, the uncertainty involving procurement and transportation can be translated into a relatively deterministic one by making detailed contracts in advance once the supply-chain operation decision of a finite future time horizon has been made. Therefore, a two-stage simulation based optimization framework is proposed to deal with these two distinct uncertainties. In the first stage, a robust supply-chain operation decision is made by combining deterministic optimization and stochastic simulation of demand uncertainty. The procurement and transportation uncertainties are treated in the second stage by negotiation on the basis of decisions made in the first stage.

In addition, our approach in the first stage to cope with demand uncertainty is more suitable to address the problem considered in this paper, which involves multi-products, multiple production modes, changeover and a distribution network. The objective of the problem is to maximize profits or minimize costs in the condition of meeting the target customer satisfaction level (CSL). The stochastic probabilistic approach may not be used here due to the networked distribution centers and customers, as well as the definition of CSL. The stochastic variables are coupled with other decision variables over the calculation of CSL, thus the probability density function of the CSL formulation could not be obtained even though the probability density function of stochastic demands is given. The scenario-based approach will also fail due to the burden of stupendous scenario tree when taking into account considerable customers, multiple time periods and continuous distribution functions. Several simulation-based optimization approaches were proposed to deal with demand uncertainty by adjusting stock levels.[6−9] However, some approaches[7,8] are only suitable for simple model and make-to-stock strategy. The make-to-stock strategy means making production planning to automatically replenish inventory to the designed base-stock level at each period. In other words, the production planning can be made by simple if-then rules without the utilization of mathematical programming. Then they use a genetic algorithm (GA) to find an optimal base-stock level. It can be seen that the simple if-then rules are only suitable for simple SC models like cases with single product, no resource and no distribution[7] or with single production mode.[8] One approach[9] used GA to evaluate the effect of different policies including product safety stock on the same cases. The safety stock levels formed the chromosome in GA and were directly evaluated by simulations regardless of optimization, which means the decisions can be inferred directly from the safety stock levels. Therefore, this approach is also unsuitable for the purpose of making robust and sub-optimal operation decisions of complex SC. Compared with the aforementioned approaches, the most well-regarded one[6] for the problem addressed herein increases the safety stock levels and repeats mathematical programming at each iteration and then evaluates the performances of new decisions on the simulations until the target CSL is achieved. Our approach at the first stage introduces an additional inner loop, which only pays attention to the worst performed inventory and adjusts distributions of products without increasing production. This new strategy can increase the CSL without obvious increase of overall costs, which will be shown in the case study. It should also be emphasized that the simulator in our framework actually performs as a controller that uses if-then rules to generate the refinery's reactive actions based on the proactive decisions when facing the uncertainties, so it can be computed very fast. In contrast, the simulation module embedded scheduling optimization with a time scale of 1 month horizon[6] may suffer from complex network and numerous scenarios.

Moreover, this two-stage framework has two additional benefits. Firstly, it has been noted that major challenges in enterprise and SC optimization include the development of models for long-term SC optimization of process networks that eventually must be integrated with scheduling models.[12] Instead of integrating 1 month horizon planning and 3~5 days horizon scheduling to resolve the output production decisions from long-term SC optimization,[13,14] we give another path to fill the gap between long-term SC optimization model and scheduling model by directly disaggregating long-term SC into short-term SC operation decisions with each period of 3~5 days. Secondly, the two-stage framework suggests a new workflow to SC decision makers. Currently, uncertainties from incomplete information are formulated in advance to make more feasible decisions, which means the refinery sacrifices its interest initially for robustness. In contrast, we suggest that a refinery should make optimal decisions without the consideration of incomplete information at first, and then improve the decisions to be realistic by negotiations and further specific constraints. During this process, more and more incomplete information is reduced and transferred into explicit short-term constraints gradually. The new workflow helps a refinery minimize its sacrifice of interest.

The remainder of this paper is organized as follows. In the next section, the two-stage framework will be introduced, followed by the formulation of the three submodels involved. Then, the computational and implemental details of the framework will be described. We will illustrate and report the performance of the framework through case studies in section 5. The paper ends with concluding remarks in section 6.

2. Framework

2.1 Problem description

The expected value of the ability to meet the product needs of a customer is traditionally called the CSL. The concept of the safety stock level is widely used to deal with demand uncertainty.[6] Fig. 1 shows the conceptual relation between the CSL and the safety stock level of a product under uncertain demand.[6] The CSL is a monotonically increasing function of the safety stock level, while the inventory holding cost is a monotonically increasing function of the safety stock level. The CSL will

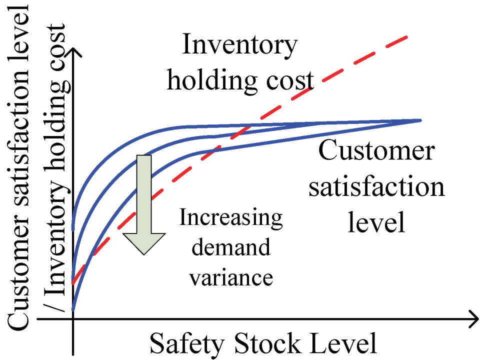


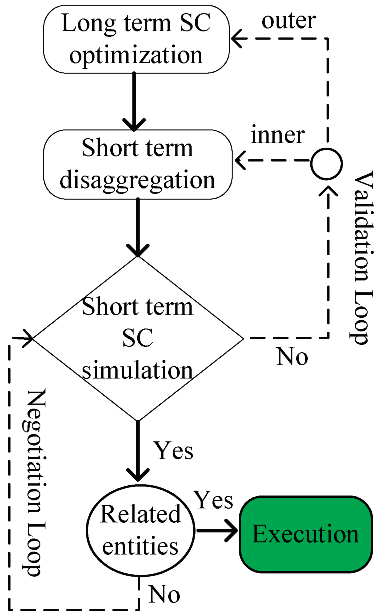
Fig. 1 – *Relation between safety stock level and customer satisfaction level or inventory holding cost (Jung et al. 2004)*

monotonically decrease when demand variance increases. The safety stock level provides a way to reach high CSL even under high demand variance. The trade-off between maximizing CSL and minimizing inventory-holding cost under demand uncertainty thus results in a constrained stochastic optimization problem. In this paper, the safety stock level is adopted to promote the robustness of the SC operation decision under uncertainties.

2.2 Two-stage framework with validation and negotiation

This paper focuses on how to make suboptimal time dependent SC operation decisions under uncertainties, which can achieve a target CSL through the assistance of tiny reactive actions from the simulator.

In a refinery, an important task associated with the supply chain department and marketing department is to make long-term SC decisions based on the predictions of production demand and raw material/product prices. Regardless of new investment of producing units or inventory capacities (actually, it is one of the study fields about SC management), additional profit of a horizon besides normal sales revenue can be obtained by utilizing the variance of material prices among different periods. Based on the long-term planning, the specific arrangements of time dependent short-term supply, inventory and delivery decisions should be made with the cooperation of departments in charge of the supply chain, manufacturing and transport. They aim at minimizing the overall costs when disaggregating the decided supply, production and sale amount of a coming long-term period into executable short-term arrangements. Short-term decisions are made for the near future so that the material prices already can be considered to be deterministic. A sequence of suboptimal and robust short-term arrangements are more desired than one globally optimal but weak to



F i g . 2 – *A supply chain decision-making framework with validation and negotiation*

uncertainties, because it is hard to adjust once suggested arrangements are executed.

Fig. 2 depicts the proposed framework for decision making of SC operation. Long-term SC optimization model, short-term SC disaggregation model and short-term SC simulation model constitute three submodels of the framework, where the simulation model is a rule-based system to generate different reactive actions for uncertain realizations. The structure, content and function of these models will be explained in detail in the next section. At the first stage of the framework, a validation loop consisting of inner loop and outer loop was adopted to adjust SC operation decisions through the combination of deterministic optimization and simulation with demand uncertainty. At the second stage, the supply and transportation arrangements from the validated solution will be transferred into orders and negotiated with suppliers and transport companies. The solution can finally be executed only if it passes such a negotiation loop, otherwise, extra constraints coming from the newly revealed incomplete information during the negotiation should be added to the short-term disaggregation model, and then a new process of decision making, validating and negotiating will be repeated. The process of decision making is shown as follows, many details of which are given in session 4:

Step1: Make long-term SC decisions by running long-term SC optimization model.

Step2: Disaggregate step1's decisions of a coming long period into short-term time dependent arrangements by running short-term SC disaggregation model.

Step3: Run the short-term arrangements of step2 on a series of simulations to evaluate their feasibility and robustness under demand uncertainty. Monte Carlo method is used to sample the stochastic parameters of the demand uncertainty. The expected value of CSL will be calculated over simulations. If the index CSL satisfies the target, then jump to step5. Otherwise, go to step4.

Step4: Run validation loop, which includes an inner loop and an outer loop. The safety stock level of some equipment will be adjusted during validation loop to promote the index CSL to the target. The three submodels may be repeatedly used during this step.

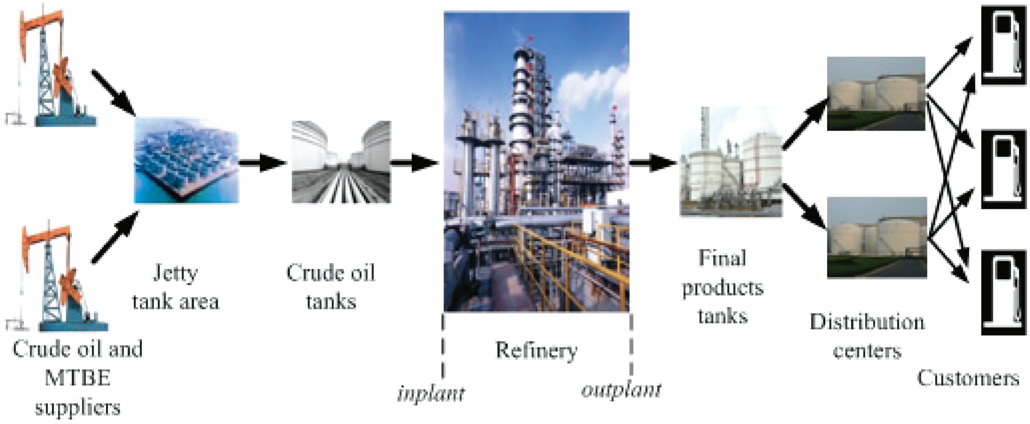
Step5: Negotiate with related business entities for the feasibility of the SC operation decisions. If successful, make order of procurement and transportation and execute following the decisions. Otherwise, trigger the negotiation loop described in section 4 until the final feasible operation decisions are generated.

3. Formulation of three submodels

The three submodels included in the framework are formulated in detail in this section.

3.1 Long-term supply-chain optimization model

The formulation of this model is a variant of the deterministic mixed-integer linear programming model proposed for supply-chain planning.[15] Since the materials are only transformed at the refinery node in the whole supply chain network, the feed-yield relationship for each node (processor)[15] is replaced by movement relationships for the sake of convenience. Long-term SC optimization model aims at maximizing the overall profit of the long-term horizon. This model is a deterministic model based on the predictions of prices of raw materials and products, demands of products in each long time period *h*. As shown in Fig. 3, all of the nodes in a supply chain such as oil sources, MTBE suppliers, jetty tank areas, oil tanks, manufacturing plants, product tanks, distribution centers and customers are denoted by sites *s*, each of which may involve several products *i*. It should be emphasized that a manufacturing plant is modeled by a pair of feedstock entry-bound and product exit-bound, which belong to the subset of sites $s^{outplant}$ and $s^{inplant}$ respectively. The manufacturing process from feedstock to products mainly depends on the production modes. In real refineries, the mix ratios of crudes



F i g . 3 – *General supply-chain network*

always form into some fixed preferred patterns due to little variations of properties of the same crude, requirements of stationary and security of production and limits of eligibility for products' various properties, such as sulfur content, octane number or cetane number. Each production mode includes the ratio of each kind of crude in mixed feedstock and the yield of each product. For SC optimization and simulation, a detailed model based on key component considerations and True Boiling Point curve is unnecessary.[16] A long time period h is identical to the short time horizon. The production scheduling time period is denoted by k, which is the minimum time unit of run length for a production mode. We assume that changeover of production modes only occurs at the beginning or end of a scheduling period, and a short SC time period t comprises N_k continuous production scheduling periods. Then the total run length of all production modes in a long time period h is no more than $N_t N_k$. In both long-term SC optimization model and short-term disaggregation model, the predicted demands are not allowed to be satisfied in the later periods. The shortage of inventories and demands are penalized in the objective function. The transportation costs are assumed to be following piecewise linear functions, which can be modeled conveniently using Special Ordered Sets of type II (SOS2).[17] It should be noticed that a fixed cost function can also be modeled by setting $B_0 = 0$, $B_1 = const$ and $VC_0 = 0$ in SOS2, where *const* may be any constant larger than the maximum $F_{s,s',i,v,h}$ or $F_{s,s',i,v,t}$. The decision variables of long-term SC optimization model are $F_{s,s',i,v,h}$, $IV_{s,i,h}$, $RL_{m,h}$ and $Pro_{m,h}$. The objective function involves revenues from sales, procurement costs, transportation costs, inventory-holding costs and penalties of shortages from demands and inventories. The long-term SC optimization model is mathematically constructed as follows:

Objective function

Maximize:

$$\begin{aligned} f_L = & \sum_{s,i,c,h} \mu_{i,h} F_{s,c,i,h} - \sum_{s \in S^{OS}, s',i,h} p_{s,i,h} F_{s,s',i,h} - \\ & - \sum_{<s,s'v> \in Link,\, z \le z^{\max}_{s,s',v}} q_{s,s',v,z} (FC_{s,s',v,z} + VC_{s,s',v,z} B_{s,s',v,z}) - \\ & - N_T \sum_{s,i,h} hc_{s,i} IV_{s,i,h} - \sum_{s,i,h} ip_{s,i} IV^{\Delta}_{s,i,h} - \sum_{c,i,h} dp_i D^{\Delta}_{c,i,h} \end{aligned} \tag{1}$$

Subject to

Manufacturing constraints:

$$F_{s,s',i,v,h} = \sum_m Pro_{m,h} Y_{i,m} \qquad \forall s \in S^{outplant} \tag{2}$$

$$F_{s,s',i,v,h} = \sum_m Pro_{m,h} X_{i,m} \qquad \forall s' \in S^{inplant} \tag{3}$$

$$RL_{m,h} Pro^L \le Pro_{m,h} \le RL_{m,h} Pro^U \tag{4}$$

$$\sum_m RL_{m,h} \le N_t N_k \tag{5}$$

Supply chain constraints:

$$IV_{s,i,h} = IV_{s,i,h-1} + \sum_{s',i,v} F_{s',s,i,v,h} - \sum_{s'',i,v} F_{s,s'',i,v,h} \tag{6}$$

$$D^{\Delta}_{c,i,h} \ge D_{c,i,h} - \sum_{s,v} F_{s,c,i,v,h} \tag{7}$$

$$\sum_{s,v} F_{s,c,i,v,h} \le D_{c,i,h} \tag{8}$$

$$O^L_{s,i} \le \sum_v F_{s,s',i,v,h} \le O^U_{s,i} \qquad \forall s \in S^{OS} \tag{9}$$

$$IV^{\Delta}_{s,i,h} \ge IV^S_{s,i} - IV_{s,i,h} \qquad \forall <s,i> \in SI \tag{10}$$

Piecewise linear transportation cost constraints:

$$\sum_{z \le z^{\max}_{s,s',v}} q_{s,s',v,z} B_{s,s',v,z} = F_{s,s',i,v,h} \quad \forall \langle s,s',v \rangle \in Link \tag{11}$$

$$\sum_{z \le z^{\max}_{s,s',v}} q_{s,s',v,z} = 1 \qquad \forall \langle s,s',v \rangle \in Link \tag{12}$$

Lower bound constraints:

$$F_{s,s',i,v,h},\ RL_{m,h},\ IV_{s,i,h},\ IV^{\Delta}_{s,i,h},\ D^{\Delta}_{c,i,h} \ge 0 \tag{13}$$

Upper bound constraints:

$$IV_{s,i,h} \le IV^{U}_{s,i} \qquad \forall \langle s,i \rangle \in SI, \qquad \sum_{i} IV_{s,i,h} \le Cap_s \qquad \forall \langle s,i \rangle \in SI \tag{14}$$

3.2 Short-term supply-chain disaggregation model

The short-term SC disaggregation model aims at minimizing the overall costs when disaggregating the amounts of procurements, productions and sales of a selected long time period h^* into time dependent short-term operation arrangements. This model receives the values of procurement F_{s,s',i,v,h^*} ($\forall s \in S^{OS}$) and manufacturing plans Pro_{m,h^*} and RL_{m,h^*} ($\forall m \in M$) of the long time period h^* from the long-term SC optimization model. The arrangements of short-term SC should be constrained by some long-term SC decisions, which are shown in eqs. (18), (21), (28). We also assume that the predicted demands of the short-term horizon accord with that of the long time period h^*, see eq. (27). An obvious difference between the objective function of long term and short term model is that the latter takes changeover costs of production mode into consideration. eq. (22) and (23) count the overall number of changeover happened. Actually, the piecewise linear functions describing transportation costs are mainly effective in this short-term model, because the delivery amounts of a long time period are always large enough to locate in the most right-hand zone of the piecewise zones.

Objective function

Minimize:

$$\begin{aligned} f_S = & \sum_{s \in S^{OS}, s', i, t} p_{s,i,h^*} F_{s,s',i,t} + \\ & + \sum_{\langle s,s'v \rangle \in Link,\ z \le z^{\max}_{s,s',v}} q_{s,s',v,z} (FC_{s,s',v,z} + VC_{s,s',v,z} B_{s,s',v,z}) + \\ & + \sum_{s,i,t} hc_{s,i} IV_{s,i,t} + \sum_{s,i,t} ip_{s,i} IV^{\Delta}_{s,i,t} + \sum_{c,i,t} dp_i D^{\Delta}_{c,i,t} + \\ & + \sum_{m,t,k} \xi CH_{m,t,k} \end{aligned} \tag{15}$$

Subject to

Manufacturing constraints:

$$F_{s,s',i,v,t} = \sum_{m} Pro_{m,t} Y_{i,m} \qquad \forall s \in S^{outplant} \tag{16}$$

$$F_{s,s',i,v,t} = \sum_{m} Pro_{m,t} X_{i,m} \qquad \forall s' \in S^{inplant} \tag{17}$$

$$\sum_{t,k} Z_{m,t,k} = RL_{m,h^*} \qquad \forall m \in M \tag{18}$$

$$\sum_{m} Z_{m,t,k} \le 1 \tag{19}$$

$$Pro^{L} \sum_{k} Z_{m,t,k} \le Pro_{m,t} \le Pro^{U} \sum_{k} Z_{m,t,k} \tag{20}$$

$$\sum_{t} Pro_{m,t} = Pro_{m,h^*} \qquad \forall m \in M \tag{21}$$

$$CH_{m,t,k} \ge Z_{m,t,k} - Z_{m,t,k-1} \qquad \forall k \ge 2 \tag{22}$$

$$CH_{m,t,k} \ge Z_{m,t,k} - Z_{m,t-1,k} \qquad \forall k = 1 \tag{23}$$

Supply chain constraints:

$$IV_{s,i,t} = IV_{s,i,t-1} + \sum_{s',i,v} F_{s',s,i,v,t} - \sum_{s'',i,v} F_{s,s'',i,v,t} \tag{24}$$

$$D^{\Delta}_{c,i,t} \ge D_{c,i,t} - \sum_{s,v} F_{s,c,i,v,t} \tag{25}$$

$$\sum_{s,v} F_{s,c,i,v,t} \le D_{c,i,t} \tag{26}$$

$$\sum_{t} D_{c,i,t} = D_{c,i,h^*} \qquad \forall \langle c,i \rangle \in SI \tag{27}$$

$$\sum_{t} F_{s,s',i,v,t} = F_{s,s',i,v,h^*} \qquad \forall s \in S^{OS} \tag{28}$$

$$IV^{\Delta}_{s,i,t} \ge IV^{S}_{s,i} - IV_{s,i,t} \qquad \forall \langle s,i \rangle \in SI \tag{29}$$

Piecewise linear transportation cost constraints:

$$\sum_{z \le z^{\max}_{s,s',v}} q_{s,s',v,z} B_{s,s',v,z} = F_{s,s',i,v,t} \quad \forall \langle s,s',v \rangle \in Link \tag{30}$$

$$\sum_{z \le z^{\max}_{s,s',v}} q_{s,s',v,z} = 1 \qquad \forall \langle s,s',v \rangle \in Link \tag{31}$$

Lower bound constraints:

$$F_{s,s',i,v,t},\ IV_{s,i,t},\ IV^{\Delta}_{s,i,t},\ CH_{m,t,k},\ D^{\Delta}_{c,i,t} \ge 0 \tag{32}$$

Upper bound constraints:

$$IV_{s,i,t} \le IV^{U}_{s,i} \qquad \forall \langle s,i \rangle \in SI, \qquad \sum_{i} IV_{s,i,t} \le Cap_s \qquad \forall \langle s,i \rangle \in SI \tag{33}$$

3.3 Short-term supply-chain simulation model

Long-term SC optimization model and short-term SC disaggregation model are both deterministic models, the demand uncertainty is performed by the short-term SC simulation model. It aims to validate the feasibility of short-term time dependent arrangements under demands variations. The input information of simulation model includes the procurement arrangements of raw materials $F_{s,s',i,v,t}$ $(\forall s \in S^{OS})$, the consumptions of raw materials $F_{s,s',i,v,t} = \sum_m Pro_{m,t} X_{i,m}$ $(\forall s \in S^{inplant})$ and the scheduling arrangements of production modes $Z_{m,t,k}$. These inputs are all inherited from the disaggregated results except that $F_{s,s',i,v,t}$ $(\forall s \in S^{OS})$, will be replaced by the negotiated arrangements when using simulation during the negotiation loop. The stochastic variables of demands are denoted by $D^{sim}_{c,i,t}$. It is assumed that the possible demands are around the predicted ones. Then the stochastic demands can be modeled as eq. (34)–(35):[16]

$$D^{sim}_{c,i,t} = D_{c,i,t}\eta_{c,i,t} \tag{34}$$

$$\eta_{c,i,t} = f(\eta^{seed}_{c,i,t})_{st} \quad \eta_{c,i,t} \in [1 - FIL_{c,i}, 1 + FIL_{c,i}] \tag{35}$$

In each iteration of simulations, $D^{sim}_{c,i,t}$ is varying by random sampling $\eta^{seed}_{c,i,t}$ and no limit for the type of probability distribution. The simulation model focuses on the feasibility (satisfying the demands) of short-term arrangements rather than the overall costs or the violations of safety stock level. Reactive actions are available in real refinery by adjusting the flow rates of products from distribution centers to customers in time due to the temporarily generated short-term demand variations. If the stochastic demands of a customer are less than predicted ones, then we assume that the deliveries from different distribution centers to this customer decrease at the same rate according to the disaggregation arrangements. Otherwise, more than disaggregated amounts of products should be delivered to this customer. In that case, the safety stock level of distribution centers can be violated in order to quickly meet the extra demands in the simulation model. In the real world, distribution centers are always far away from each other and one distribution center is in charge of one region. Therefore, it is assumed that the extra demands of a customer can only be satisfied by its nearest distribution center. The transportation amounts can be increased until the inventory of its nearest distribution center decrease to be empty. As the disaggregation model, the demand shortage should not be satisfied in the subsequent periods. Actually, such a simulator can be considered as a controller running following if-then rules.

4. Computational and implemental details of the framework

In this section, the details of the framework proposed in section 2 are explained, including the calculation of customer satisfaction level, the processes of validation and negotiation loops and the implementation of the framework.

4.1 Performance evaluation of short-term supply-chain arrangements

In order to measure the feasibility of the time dependent short-term disaggregation arrangements, CSL is calculated from the arrangement performances on the short-term SC simulation model under various stochastic samples. The aim for improving the CSL is implied as decreasing demand shortage penalties in both the long-term optimization and short-term disaggregation models, while in the simulation model the CSL is explicitly calculated. The CSL is the expectation performance under various stochastic realizations of demands uncertainties. They are evaluated on the whole short-term horizon. The calculations of CSL are shown as follows, including three scales:

$$J_{c,i} = E\left[\frac{1}{\sum_t \operatorname{sgn}(D^{sim}_{c,i,t})} \sum_t \frac{\sum_{s,v} F^{+}_{s,c,i,v,t}}{D^{sim}_{c,i,t}}\right] \tag{36}$$

$$\forall c \in C \text{ and } i \in I^{FP} \text{ and } D^{sim}_{c,i,t} \neq 0$$

$$J_i = E\left[\frac{1}{|C|}\sum_c J_{c,i}\right] \qquad \forall i \in I^{FP} \tag{37}$$

$$J = E\left[\frac{1}{|I^{FP}|}\sum_i J_i\right] \tag{38}$$

Where $J_{c,i}$ stands for the expected value of CSL of the specific customer c and product i, J stands for the expected value of CSL of the specific product i and J stands for the expected value of CSL of the overall customers and products. In addition, sgn(x) is the sign function, which takes 1, 0, -1 respectively in case of $x > 0$, $x = 0$ and $x < 0$. $|C|$ and $|I^{FP}|$ respectively represent the number of customers and products. The short-term SC arrangements can be considered to be feasible if the global CSL J achieves to the target CSL J^{target}.

The stochastic realization problem of uncertainties identifies how to select the seeds $\eta_{c,i,t}^{seed}$ and the formation of stochastic function $f(\cdot)_{st}$ in eq. (35). Obviously, it is the general formulation and many different probability density functions can be included. The selection of $f(\cdot)_{st}$ may mainly rely on the statistic of historical data. In the case study of this paper, it is assumed that $\eta_{c,i,t}$ acts as uniform distributions in the specific range $[1-FIL_{c,i}, 1+FIL_{c,i}]$. The selection of seeds adopts the Monte Carlo method.

4.2 Validation loop

The short-term SC operation arrangements should be validated under uncertain environments whether the CSL J can reach J^{target}. If this fails, the validation loop is triggered to adjust the short-term arrangements by modifying the safety stock levels of distribution centers. This strategy is feasible due to the relationship of customer satisfaction level and safety stock level described in section 2. The validation loop is comprised by an outer loop and an inner loop. At first, we only make effort on the disaggregation model by adjusting the safety stock level of the individual distribution center in the inner loop, which means the total producing amount of products in the whole short-term horizon are maintained and its specific distributions in distribution centers are modified. In the iterations, the safety stock level of a specific pair of distribution center and stored product $<s^*, i^*>$ will be increased at first, which is the nearest neighbor of the most disappointed customer c^* whose CSL J_{c^*,i^*} has the largest deviation from target CSL. Since the producing amount of a product in the whole short-term horizon keeps invariant, the increase of one distribution center's storage must result in decrease of others'. If the decrease occurs on the distribution center with redundant storage, obviously the global CSL J will be improved. If the decrease occurs on the distribution center with insufficient storage, excessive decrease may result in this distribution center not being able to satisfy its customers under uncertainty. In spite of this, at least a little increase of safety stock level of $<s^*, i^*>$ can improve the global J because s^* is the weakest point. Once the global J decreases out of the expectation, excessive increase of its safety stock level must happen. Then, eq. (39) in the inner loop can automatically correct the excessive iterative step length because $\alpha_2(J(l,n) - J(l,n-1)) < 0$ holds when $J(l,n) \leq J(l,n-1)$ happens. The tasks done when the case $J(l,n) \leq J(l,n-1)$ happens in step 3 can guarantee the realizations of the improvement of global J for each selected s^*, even some iterations should be made in this process. The iterative step lengths of safety stock levels are in proportion to the deviations of CSL as shown in eqs. (39) and (40). It is noted that the adjustments in the inner loop usually do not impact the overall inventory holding costs in the horizon because they only change the distributions in different sites.

Even though inner loop can improve the customer satisfaction level, its effect is sometimes limited due to the maintenance of the long-term results. In contrast, the outer loop can remarkably improve the CSL by increasing the producing amounts, but at the same time it will increase the costs compared to the inner loop. The validation loop will jump to the outer loop from the inner loop when the efforts of the inner loop suffer bottleneck, which is controlled by step 3 of the inner loop. It can be noted that the safety stock levels of distribution centers increase synchronously at each iteration according to a distribution factor $\beta_{s,i}$. The distribution factor relies on the number of customers a distribution center in charge and the variations of demands of these customers. The distribution centers in touch with the customers with lower CSL in the simulations should have larger distribution factors.

The validation loop will continue until one of the following two conditions holds: the global CSL J exceeds its target value; the sum of overall step lengths of all sites is less than a specified tolerance during the outer loop. In a word, both of the inner and outer loops try to improve CSL by manipulating the safety stock levels $IV_{s,i}^S(l,n)$ of distribution centers. The inner and outer loops are shown as follows.

Inner loop:

Step 1: Run the short term SC disaggregation model with the safety stock level $IV_{s,i}^S(l,n)$, for all $s \in DC$ and $<s,i> \in SI$. In the initial iteration, $l = 0$, $n = 0$ and $IV_{s,i}^S(0,0) = IV_{s,i}^S$.

Step 2: Run a sufficient number of Monte-Carlo sampling based simulations with demand uncertainties to obtain the expected customer satisfaction levels $J_{c,i}(l,n)$, $J_i(l,n)$ and $J(l,n)$ of the disaggregation arrangements of step 1.

Step 3: Check if $J(l,n) \geq J^{target}$ stop both the inner and outer loop.

Or if $J(l,n) \leq J(l,n-1)$, update the new safety stock level of

$$IV_{s^*,i^*}^S(l,n+1) = IV_{s^*,i^*}^S(l,n) + \\ + \alpha_2(J(l,n) - J(l,n-1)) \tag{39}$$

Let $J(l,n) = J(l,n-1)$ and go to step 1.

Or if $|J(l,n) - J(l,n-1)| < \varepsilon_1$ and $J(l,n) < J^{target}$, stop the inner loop and go to the outer loop.

Or, continue.

Step 4: Find the most disappointed customer and the corresponding product, $< c^*, i^* > = \arg\max_{c,i}(J_i^{target} - J_{c,i}(l,n))$. Find the distribution center s^* with the nearest distance to customer c^*. Set the new safety stock level of s^* using eq. (40).

$$IV^S_{s^*,i^*}(l,n+1) = IV^S_{s^*,i^*}(l,n) + \\ + \alpha_1 \beta_{s^*,i^*}(J_{i^*}^{target} - J_{c^*,i^*}(l,n)), \tag{40}$$

And for all other s and i, $IV^S_{s,i}(l,n+1) = IV^S_{s,i}(l,n)$. Set $n = n+1$ and go to step 1.

It should be emphasized that in the inner loop, $\alpha_1 > 0$ and $\alpha_2 > 0$ should be held.

Outer loop:

Step 1: Update $IV^S_{s,i}(l+1,0) = IV^S_{s,i}(l,0) + \alpha_3 \beta_{s,i}(J_i^{target} - J_i(l,0))$, for all s and i.

Step 2: If $\sum_{s,i} | IV^S_{s,i}(l+1,0) - IV^S_{s,i}(l,0)| < \varepsilon_2$ stop both the inner and outer loop. Otherwise, run long-term SC optimization model with the new safety stock levels and go to step 1 of the inner loop.

Negotiation loop

As you know, the raw material suppliers and transport companies are individual business organizations, so they also pursue maximum profit when facing the order requirements from various refineries. Besides fixed long-term (may last one year or even more) contacts on supply or transportation, a refinery sometimes cannot obtain the concrete information about accessibility before concrete orders about short-term time dependent arrangements are made. Thus, the short-term SC arrangements after validation need to be negotiated with these business entities. The negotiation process is as follows:

Step 1: Make orders according to validated short-term SC arrangements.

Step 2: If all of the orders can be dealt as expectation after negotiations, execute the arrangements and stop the loop. Otherwise, modify the short-term arrangements about some local amount and time information according to negotiated results, and then rerun a sufficient number of simulations with demand uncertainties to obtain the expected value of CSL $J(l,n)$.

Step 3: If $J(l,n) \geq J^{target}$ execute the modified arrangements. Otherwise, increase extra supply or transportation constraints about amount and time to the short-term SC disaggregation model according to negotiated results and run this modified disaggregation model, and then go to step 1 of the inner validation loop.

4.4 Implementation

The implementation of the framework proposed in this paper includes: the three submodels respectively for long-term SC optimization, short-term disaggregation and short-term SC simulation, the database and the computation control module for managing validation loop and negotiation loop, as shown in Fig. 4. The three submodels all have relatively independent functions as described in section 3 and managed by the computation control module.

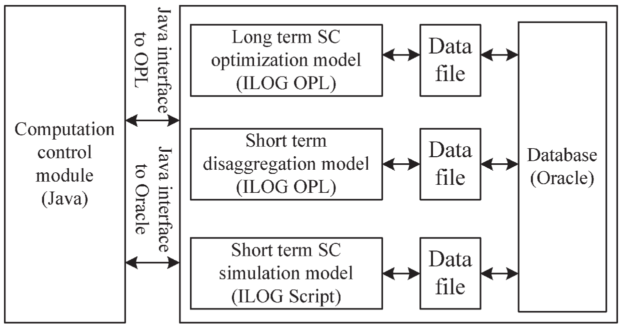
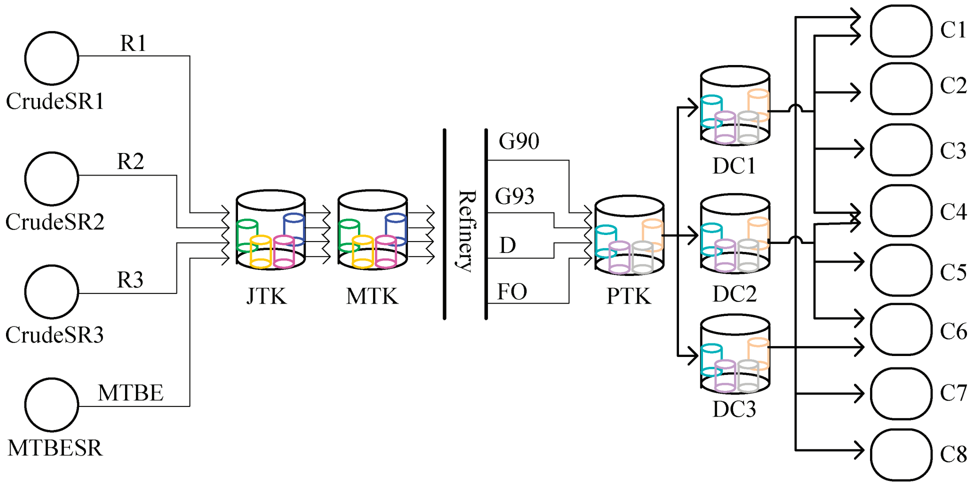


Fig. 4 – *Information flow among computational components*

The computational framework is mainly executed on the ILOG tools. The long-term SC optimization and short-term disaggregation models are both mixed integer linear programming (MILP) models and can be solved by the mathematical programming engine ILOG Cplex. ILOG's Optimization Programming Language (ILOG OPL) provides a natural representation of optimization models, requiring far less effort than general-purpose programming languages. Therefore, both the long-term optimization and short-term disaggregation models are coded in ILOG OPL. In addition, the ILOG Script for OPL is an embedded JavaScript implementation that provides the "non-modeling" expressiveness of OPL to implement our simulation model. The three submodels are instanced by corresponding ILOG data file, which can read from or update the database using SQL language. In our case, we used Oracle as the database to describe the information of the case problem and store the dynamic results. For example, the solution of



F i g . 5 – *Simplified supply chain network of a refinery*

$RL_{m,h}$ in long-term optimization will be stored to oracle for later use by short-term disaggregation model. ILOG also provides Java interface for OPL to control how models are instantiated and solved or modify the model data between one solution and the next. It is also noted that Oracle provides Java DataBase Connectivity standard (JDBC) to enable Java to query from and update the database. Therefore, the computation control module is implemented in Java for the sake of convenient interaction with both ILOG OPL and Oracle. The computation control module mainly plays roles in:

– Organizing the model files and data files

– Preprocessing and post-processing the model files or database to update some information if necessary

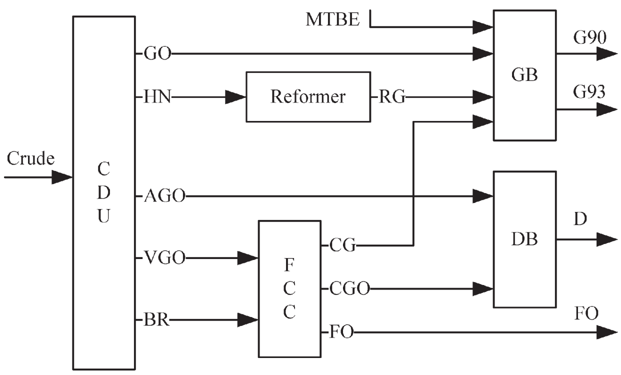
– Controlling the iterative flow of the outer and inner validation loop and negotiation loop by updating model's input data and constraints parameters and re-organizing the model and data files

– Generating Monte-Carlo stochastic demands for the simulation model and calculating the hierarchical CSL.

Additionally, it should be noted that the SOS2 function can be directly implemented by the piecewise linear functions using ILOG OPL. The piecewise linear function can be obtained in ILOG OPL only by giving the break point and slope of each piecewise zone and the initial point of the piecewise curve. The experiments in section 5 were made on ILOG Cplex11.0 and ILOG OPL Development Studio 5.5. The relative mipgap tolerance and time limit of the Cplex parameters were set to 0.4 % and 700 s for the short-term disaggregation model on a machine with 1.59GHz AMD Turion 64 X2 cpu and 512 MB memory.

5. Case study

The simulation-based optimization framework for SC operation is illustrated in this section through case studies. The refinery under consideration processes three crudes and one more raw material methyl tertiary butyl ether (MTBE) to make four products. The supply chain network is shown as Fig. 5, where R1~ R3 are three crudes bought from three crude sources CrudeSR1~ CrudeSR3, JTK, MTK and PTK respectively denote tank areas of jetty, refinery feedstock and products, DC1~DC3 are three distribution centers, and C1~C8 stand for eight customers or sale regions. The refinery produces four products 90# gasoline (G90), 93# gasoline (G93), diesel (D) and fuel oil (FO). Fig. 6 illustrates the schematic of a refinery. The refinery contains the following main units: crude distillation unit (CDU), Reformer, fluid catalytic cracker (FCC), gasoline blending pool (GB) and diesel blending pool (DB). Crude oils are separated into five fractions by CDU, namely, gross overhead (GO), heavy naphtha (HN), atmospheric gas oil (AGO), vacuum gas oil (VGO) and bottom residue (BR). The HN then forms the feed to the reformer



F i g . 6 – *Schematic of a refinery*

to produce reformer gasoline (RG). The VGO and BR enter into FCC as feed to produce crack gasoline (CG), crack gas oil (CGO) and product FO. MTBE, GO, RG and CG forms the feed streams of GB to produce G90 and G93. AGO and CGO enter DB to generate product D.

Table 1 presents the prices of raw materials and products. The feedstock consumption ratio and production yields of the four production modes in the refinery are respectively shown in Tables 2 and 3. Table 4 gives the demand prediction variations of eight customers over different products, namely, the settings of forecast inaccuracy limit FIL. Table 5 presents the parameters such as inventory upper bounds, safety stock levels, initial inventories, inventory holding-costs and safety stock level violation penalties involved with the sites belonging to S^{IV}. In this case, the long-term horizon consists of four periods and each such long time period is decomposed into 10 short time periods. Meanwhile, every short time period includes 9 scheduling periods. The case aims to present robust SC operation decisions of the first short-term horizon based on the planning of long-term horizon. Tables 6 and 7 respectively give the forecast demands data of the long-term horizon and short-term horizon of the first long time period. The piecewise linear transportation cost data are shown in Table 8, where 'inf' stands for infinity, herein particularly means positive infinity. Other parameters involved in this case are listed in Table 9.

Table 1 – *Prices of materials*

Materials (I)	Type	Price (k$/kbbl)
R1	I^{RM}	120
R2	I^{RM}	124
R3	I^{RM}	116
MTBE	I^{RM}	153
G93	I^{FP}	160
G90	I^{FP}	153
D	I^{FP}	155
FO	I^{FP}	145

Table 2 – *Feedstock ratios of production model*

Mode (m)	Crude			
	R1	R2	R3	MTBE
m1	0.65	0.3	0	0.05
m2	0.3	0.5	0.1	0.1
m3	0.3	0.2	0.5	0
m4	0.15	0.25	0.6	0

Table 3 – *Product yields of production modes*

Mode (m)	Product			
	G90	G93	D	FO
m1	0.31	0.17	0.32	0.14
m2	0.19	0.29	0.29	0.17
m3	0.23	0.15	0.43	0.13
m4	0.14	0.21	0.36	0.24

Table 4 – *Forecast inaccuracy limits (FIL) data. Unit: %*

Product	C1	C2	C3	C4	C5	C6	C7	C8
G90	7	35	12.5	8	12	11	11	7.5
G93	9	7	9	9	7	35	44	40
D	10	7	10	12	14	20	11	7
FO	31	32	34.5	24	19	17.5	16.5	16

Table 5 – *Configurations of sites with inventories*

Site (s)	Material (i)	$IV^U_{s,i}$ (kbbl)	$IV^S_{s,i}$ (kbbl)	Initial inventory (kbbl)	Holding cost (k$/kbbl)	Inventory penalty (k$/kbbl)
JTK	R1	10000	800	1000	0.3	230
JTK	R2	10000	800	1000	0.3	230
JTK	R3	10000	800	1000	0.3	230
JTK	MTBE	4000	400	600	0.4	230
MTK	R1	20000	3000	4500	0.3	250
MTK	R2	20000	3000	4500	0.3	250
MTK	R3	20000	3000	4500	0.3	250
MTK	MTBE	8000	800	1200	0.4	300
PTK	G90	5000	500	1000	0.4	280
PTK	G93	5000	500	1000	0.45	280
PTK	D	5000	500	1000	0.4	280
PTK	FO	5000	500	1000	0.4	280
DC1	G90	15000	200	1500	0.4	300
DC1	G93	15000	200	1500	0.45	300
DC1	D	15000	200	1500	0.4	300
DC1	FO	15000	200	1500	0.4	300
DC2	G90	15000	200	1500	0.4	300
DC2	G93	15000	200	1500	0.45	300
DC2	D	15000	200	1500	0.4	300
DC2	FO	15000	200	1500	0.4	300
DC3	G90	15000	200	1500	0.4	300
DC3	G93	15000	200	1500	0.45	300
DC3	D	15000	200	1500	0.4	300
DC3	FO	15000	200	1500	0.4	300

Table 6 – *Demand forecast for a sequence of four long-term periods*

Product	Long period	Customer							
		C1	C2	C3	C4	C5	C6	C7	C8
G90	1	2400	2500	900	700	2000	2000	800	2300
	2	2400	2500	900	700	2000	2000	800	2300
	3	2600	2500	950	700	2000	2000	800	2300
	4	2400	2300	900	700	2000	2000	800	2300
G93	1	1800	1600	1000	1200	1700	1700	2900	2800
	2	1800	1600	1100	1200	1700	1700	2900	2800
	3	1900	1700	1000	1200	1700	1700	2900	2800
	4	1800	1600	1000	1200	1700	1700	2900	2800
D	1	1800	2000	1900	2000	2000	2200	2100	1800
	2	1600	2200	1900	2000	2000	2200	2100	1800
	3	1600	1900	2200	2000	2200	2200	2100	1800
	4	1600	2000	2000	2100	1900	2200	2100	1800
FO	1	1800	2800	2700	2200	1800	900	1900	1200
	2	1800	2200	2500	2000	1800	900	1900	1200
	3	1600	2400	2700	1900	1800	900	1900	1200
	4	1800	2500	2700	2300	1800	900	1900	1200

Table 8 – *Piecewise linear transportation cost data*

Source	Destination	Vehicle	B1 (kbbl)	Slope1 (k$/kbbl)	B2 (kbbl)	Slope2 (k$/kbbl)	B3 (kbbl)	Slope3 (k$/kbbl)
CrudeSR1	JTK	Ship	1	200	2000	5	inf	4.6
CrudeSR2	JTK	Ship	1	200	2000	4	inf	3
CrudeSR3	JTK	Ship	1	200	2000	4.5	inf	3.5
MTBESR	JTK	Train	1	150	500	5.5	inf	4.8
PTK	DC1	Train	1	100	2000	4	inf	3
PTK	DC2	Train	1	100	2000	4.4	inf	3.7
PTK	DC3	Train	1	100	2000	4.6	inf	3.9
DC1	C1	Truck	inf	2				
DC1	C2	Truck	inf	3				
DC1	C3	Truck	inf	3.1				
DC1	C4	Truck	inf	3				
DC2	C4	Truck	inf	2.5				
DC2	C5	Truck	inf	2.9				
DC2	C6	Truck	inf	3.2				
DC3	C6	Truck	inf	2.7				
DC3	C7	Truck	inf	2.8				
DC3	C8	Truck	inf	2.9				
DC3	C1	Truck	inf	3				

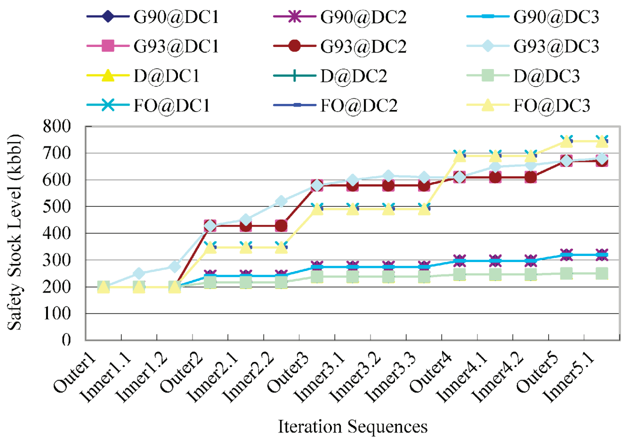
Table 7 – *Demand forecast for the first short-term horizon*

Customer	Product	Short-term period (t)									
		1	2	3	4	5	6	7	8	9	10
C1	G90	0	0	1600	0	0	0	0	800	0	0
C1	G93	0	800	0	0	0	0	0	0	0	1000
C1	D	0	0	0	0	0	1000	0	0	0	600
C1	FO	0	0	1800	0	0	0	0	0	0	0
C2	G90	0	0	0	0	1700	0	800	0	0	0
C2	G93	0	0	0	0	0	0	1600	0	0	0
C2	D	0	0	1000	0	0	0	0	1000	0	0
C2	FO	1500	0	0	1300	0	0	0	0	0	0
C3	G90	0	0	0	0	0	0	0	0	0	900
C3	G93	0	0	1000	0	0	0	0	0	0	0
C3	D	0	0	0	0	0	0	0	1900	0	0
C3	FO	0	0	1400	0	0	0	0	0	1300	0
C4	G90	0	700	0	0	0	0	0	0	0	0
C4	G93	0	800	0	0	0	0	0	0	400	0
C4	D	0	1000	0	0	0	0	0	0	1000	0
C4	FO	0	0	0	1200	0	0	0	0	1000	0
C5	G90	0	0	2000	0	0	0	0	0	0	0
C5	G93	400	0	0	0	0	0	1300	0	0	0
C5	D	0	0	0	0	2000	0	0	0	0	0
C5	FO	0	0	0	900	0	0	0	0	900	0
C6	G90	0	0	0	0	0	0	1300	0	0	700
C6	G93	0	0	1300	0	0	0	0	0	0	400
C6	D	0	0	0	0	0	1400	0	0	0	800
C6	FO	0	0	0	0	0	0	0	0	900	0
C7	G90	800	0	0	0	0	0	0	0	0	0
C7	G93	1000	1900	0	0	0	0	0	0	0	0
C7	D	0	0	1000	0	0	1100	0	0	0	0
C7	FO	0	0	1100	0	0	0	0	0	0	800
C8	G90	0	600	0	0	0	0	0	0	1700	0
C8	G93	1900	0	0	0	0	0	0	0	0	900
C8	D	0	800	0	0	0	0	0	0	0	1000
C8	FO	0	0	0	0	0	1200	0	0	0	0

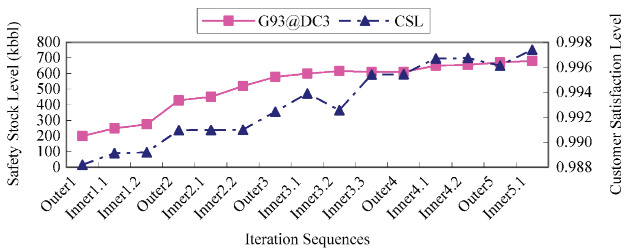
T a b l e 9 – *Values for other model parameters*

Parameter description	Notation	Value
Max. refinery throughput (kbbl/schedule period)	Pro^U	850
Min. refinery throughput (kbbl/schedule period)	Pro^L	540
Changeover fee (k$/per time)	ξ	30
Penalty for demand shortage (k$/kbbl)	dp_i	[G90:330, G93:350, D:336, FO:308]
Number of periods per short-term horizon	N_t	10
Number of scheduling periods per short-time period	N_k	9
Sites' capacity (kbbl)	Cap_s	[JTK:30000, MTK:60000, PTK:16000, DC1~DC3:50000]
Max./Min. available crude per long period (kbbl)	$O^U_{s,i}$	[CrudeSR1-R1:100000/0, CrudeSR2-R2:100000/0, CrudeSR3-R3:100000/0, MTBESR-MTBE:50000/0]

The target global CSL in this case is set to be 99.7 %. The evaluation of feasibility and robustness of the short-term SC operation decisions is made on 80 stochastic sampling simulations every time. At the beginning, the expected value of CSL on the situation that every DC has the level of 200 kbbl safety stock for every product only reaches to 98.82 %. After 15 iterations of outer and inner validation loop, the expected value of CSL reaches the target. The safety stock level data at each iteration are shown in Fig. 7, where the labels of x-axis imply the character and progress of the iterations. It can be seen that the safety stock levels involved with products G93 and FO increase faster than that of G90 or D at the iterations. The absolute fluctuation of demand relies on the multiple of forecast amount of demand and forecast inaccuracy. The large variation will result in high possibility of demand shortage and low CSL. It is noted that the demand variations of G93 for C6~C8 and FO for C1~C4 are larger than those of other customer-product pairs from Table 4 and Table 7. The lower expected values of CSL of G93 and FO for some customers make the corresponding safety stock levels increase faster than others. It also can be seen from Fig. 7 that most of the safety stock levels only change at the outer loops except that of G93 at DC3 (G93@DC3). The safety stock level of G93@DC3 is always selected for improving the global CSL J in the inner loops for its lowest CSL J_{G93}. Fig. 8 mainly illustrates the effects of inner loops on improving global CSL. We can see that at inner loops even a little change on a single safety stock can improve CSL. It can be noted that there is one exception, CSL drops against the increase of corresponding safety stock level at iteration



F i g . 7 – *The safety stock level data at each iteration*



F i g . 8 – *Global CSL versus the safety stock level of G93 at DC3 at each iteration*

inner3.2. The reason for this is that too large iterative step length has been chosen at this iteration. In other words, too many resources are used and attracted to keep the inventory of G93@DC3 at a high level. Correspondingly, the inventories of other distribution centers are no longer abundant to cope with even a little uncertain extra demand. This leads to lower CSL. Then a little lower safety stock level of G93@DC3 will be automatically allocated according to eq. (39) and high CSL will be obtained again at the next iteration.

The inventory-holding costs during the short-term horizon versus the global CSL is shown in Fig. 9. It can be seen that the inventory holding costs increase sharply at the time of outer loops and nearly remain the same at the inner loops. This is in accord with the design of inner loops, which keep the amounts of productions and just change the distribution of products. The trade-off between inventory-holding costs and CSL can be seen clearly at the time of outer loops, namely, higher CSL needs higher inventory-holding costs. Global CSL can still be promoted at the inner loops under nearly the same inventory-holding costs.

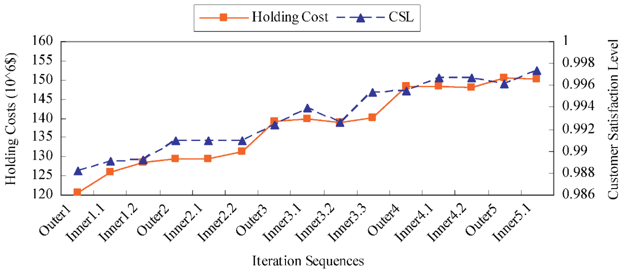


Fig. 9 – *Trade-off between inventory holding costs and the global CSL*

Fig. 10 gives the resulting total profits of four long periods at each outer loop and the total costs of the first period at each iteration. It can be seen that the profit decreases with the increase of safety stock levels at the time of outer loops. It may also be seen that the costs of the short-term disaggregation model increase following the increase of safety stock levels from Fig. 7 and Fig. 10. This illustrates that economy has to be sacrificed to trade with CSL. It can be noted that the overall costs increase sharply at each outer loop but keeps nearly stationary at each inner loop. Fig. 8 and Fig. 9 illustrate that the expected value of CSL can be promoted quite a little even at the expense of very tiny increasing cost at the inner loops, because the inner loops only trigger the running of short-term disaggregation model. In contrast with the inner loop, the outer loop triggers long-term SC optimization model and naturally increases the amount of procurement and production to reach higher safety stock levels. The adjustment of products distributions in the inner loop obviously costs much less than the increase of products in the outer loop. Compared with the equivalent isolated outer loop,[6] the advantage of combining inner loops and outer loops in our work can be demonstrated by this case.

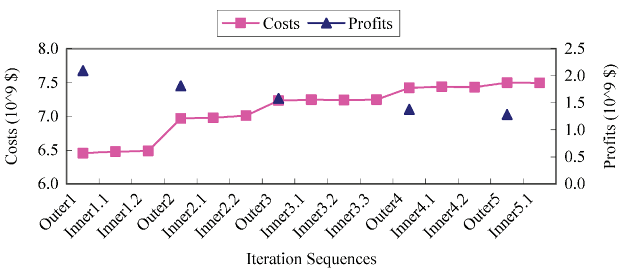


Fig. 10 – *Trajectories for the profits of multiple long periods and costs of the selected period during the iterations*

At the negotiation stage, the above decisions such as procurement and transportation arrangements will be treated as business orders to the suppliers and transport companies. The negotiation loop provides clear instructions to the following actions whether the orders are accepted or not, so the cases explaining the second stage are not included.

6. Conclusions

To survive in the highly competitive global market, refineries are focusing more attention on the SC operations. Customer satisfaction level and loyalty have been taken into consideration when making SC operation decisions. In this work, a two-stage discriminating framework was proposed for optimizing SC operation under demand uncertainty and disruption of incomplete information shared with suppliers and transport companies. A validation loop consisting of inner loop and outer loop was designed to proactively deal with demand uncertainty at the first stage. The outer loop can promote CSL a lot by increasing procurements and productions with large expense, while the inner loop can also promote CSL on the basis of outer loop only by adjusting the distribution of products with very small expense. Subsequently, the candidate decision with realistic CSL under demand uncertainty should pass to the negotiation loop before final execution. The case studies show that our framework gives an effective process to deal with two mentioned disruptions in decision making of SC operation. Our future research may focus on making SC operation decisions under other minor uncertainties.

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Nomenclature

Sets:

$I \equiv \{i\}$ – set of materials including raw materials and products

$I^{RM} \subset I$ – set of raw materials

$I^{FP} \subset I$ – set of products

$S \equiv \{s\}$ – set of sites including suppliers, jetty tank areas, crude oil tanks, manufacturing plants, product tanks, distribution centers and customers

$S^{OS} \subset S$ – set of crude oil and MTBE suppliers

$C \equiv \{c\} \subset S$ – set of customs, they are considered to be one kind of site for the sake of convenience

$DC \subset S$ – distribution centers

$S^{inplant} \subset S$ – label the plant, considering the consumption of raw materials

$S^{outplant} \subset S$ – label the plant, considering the output of products

$S^{IV} \equiv S \backslash (S^{OS} \cup S^{inplant} \cup S^{outplant} \cup C)$ – set of sites including all the inventory equipments of a refinery

$SI \equiv \{<s, i>\}$ – products that a site s possesses

$V \equiv \{v\}$ – set of vehicle mode for transportation

$Link \equiv \{<s, s', v>\}$ – two sites can be linked by transportation mode v

$Tran \equiv \{<s, s', i, v>\}$ – specific transportation tuple, denotes the feasible combination of transportation path, product and vehicle

$M \equiv \{m\}$ – set of production mode

$H \equiv \{h\} \equiv 1 \ldots N_h$ – range of time periods of long-term model

$T \equiv \{t\} \equiv 1 \ldots N_t$ – range of time periods of short-term models, its range equals to one long time period

$K \equiv \{k\} \equiv 1 \ldots N_k$ – range of scheduling time periods, its range equals to one short time period. It is assumed that a production mode at least continuously occupy a scheduling time period.

Variables:

$D_{c,i,h} / D_{c,i,t}$ – predictive demand of product $i \in I^{FP}$ for customer c due at the end of time period h or t

$D^{sim}_{c,i,h} / D^{sim}_{c,i,t}$ – supposed real demand of product $i \in I^{FP}$ for customer c due at the end of time period h or t based on predictive demand and stochastic process

$D^{\Delta}_{c,i,h} / D^{\Delta}_{c,i,t}$ – amount of shortage of product $i \in I^{FP}$ for customer c in time period h or t

$F_{s,s',i,v,h} / F_{s,s',i,v,t}$ – flow quantity of product $i \in I$ from facility s to s' via vehicle v in time period h or t where $<s, s', i, v> \in Tran$

$IV_{s,i,h} / IV_{s,i,t}$ – inventory level of product $i \in I$ at the end of time period h or t at site s

$IV^{\Delta}_{s,i,h} / IV^{\Delta}_{s,i,t}$ – deviation below safety stock level for product $i \in I$ at site $s \in S^{IV}$ in time period h or t

$J(l,n)$ – expected value of customer satisfaction level for all customers on all products at the l-th iteration of the outer validation loop and n-th iteration of the inner validation loop

$J_i(l,n)$ – expectation of mean customer satisfaction level of all customers on product $i \in I^{FP}$ at the l-th iteration of the outer validation loop and n-th iteration of the inner validation loop

$J_{c,i}(l,n)$ – expectation of customer satisfaction level of customer c on product i at the l-th iteration of the outer validation loop and n-th iteration of the inner validation loop

j^{target} – expected target value of customer satisfaction level

$Pro_{m,h} / Pro_{m,t}$ – process amount of total feedstock to the plant in time period h or t under mode m

$RL_{m,h}$ – run length of the production mode m in the long time period h. This is equal to the number of scheduling time periods occupied by mode m within h.

$Z_{m,t,k}$ – binary variable, denotes whether mode m is used in scheduling period k of short time period t

$CH_{m,t,k}$ – binary variable, denotes whether the production process is changed from other modes to mode m in scheduling period k of short time period t

Parameters:

$\alpha_1 / \alpha_2 / \alpha_3$ – iterative step lengths

$\beta_{s,i}$ – distribution factors for different distribution centers $s \in DC$ and products $i \in I^{FP}$ at iterations

$\varepsilon_1 / \varepsilon_2$ – user tolerances

$p_{s,i,h}$ – price of raw material $i \in I^{RM}$ from site s in long time period h

$\mu_{i,h}$ – revenue per unit of product $i \in I^{FP}$ in long time period h

$hc_{s,i}$ – inventory cost for holding a unit of product $i \in I$ at site s in a short time period

dp_i – penalty for shortage below demand of product $i \in I^{FP}$

$ip_{s,i}$ – penalty for inventory shortage below safety stock of material $i \in I$ at site s

$\eta_{c,i,t}$ – magnitude of variation of the actual demand from forecast demand

$\eta^{seed}_{c,i,t}$ – random seed for $\eta_{c,i,t}$

ξ – changeover cost for per change among production modes

Cap_s – capacity of site s

$FIL_{c,i}$ – forecast inaccuracy limit for demand of customer c on product $i \in I^{FP}$

$IV^U_{s,i} / IV^S_{s,i}$ – upper bound and safety stock bound of inventory level for product $i \in I$ at site $s \in S^{IV}$

$IV^S_{s,i}(l,n)$ – safety stock level for product $i \in I^{FP}$ of site $s \in DC$ at the l-th iteration of the outer validation loop and n-th iteration of the inner validation loop

$O^L_{s,i}/O^U_{s,i}$ – lower bound and upper bound of raw material $i \in I^{RM}$ a oil or MTBE supplier $s \in S^{OS}$ could supply in a long period

Pro^L/Pro^U – lower bound and upper bound of the process amount of overall feedstock to the plant in a scheduling period

$X_{i,m}$ – consumption of raw material $i \in I^{RM}$ under production mode m

$Y_{i,m}$ – yield of product $i \in I^{FP}$ under production mode m

Special ordered variables of type II (SOS2)

$q_{s,s',v,z}$ – SOS2 across zone index z of the piecewise cost function when transports per unit of product from facility s to s' via vehicle v

$B_{s,s',v,z}$ – SOS2 breakpoints, namely first point at which transportation amount from facility s to s' via vehicle v enters zones z

$FC_{s,s',v,z}$ – fixed cost (y-intercept) of linear cost segment for transportation from facility s to s' via vehicle v in zones z

$VC_{s,s',v,z}$ – variable cost (slope) of linear cost segment for transportation from facility s to s' via vehicle v in zones z

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