Managing crude oil procurement risk: An integrated operational and financial hedging framework

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Abstract
In this research, we provide an integrated operational and financial hedging strategy which uses inventory, nonlinear distillation, and three derivatives to hedge procurement risk caused by oil price volatility. Numerical experiments based on real world data are tested, which verify the benefit of the proposed approach and provide useful insights.

Keywords: Risk management, Crude Oil Procurement, Integrated Operational and Financial Hedging.

Introduction

Because of the continuously rising price, crude oil procurement cost takes up nearly 80% of the operational cost for the petroleum industry. On the other hand companies also face great procurement risks due to the great volatility of crude oil price. Figure 1 shows the price of WTI and Brent oil along with two end products gasoline and heating oil. Managers are seeking for better strategies to hedge the procurement risk meanwhile pursuing profitability.

Petroleum production shows many kinds of flexibility, such as yield ratio, blending of crude oil and end products, etc., which provides applicability to hedge procurement risks (Carneiro et al., 2010). Besides, various kinds of derivatives are also widely used, such as future contract, and call/put option which gives the owner the right, but not obligation, to buy/sell the commodity at the strike price on the expiration date (Kouvelis et al., 2013).

Some widely used methods in risk management arisen in process system engineering are stochastic programming, dynamic programming, stochastic robust programming, and fuzzy programming. This research uses stochastic programming model which incorporates with risk measure, so we mainly focus on the relevant research.

Barbaro and Bagajewicz (2003, 2004a,b) conduct series of work in the risk management in the planning of process industry. They (Bagajewicz and Barbaro, 2003) propose a two-stage stochastic programming model with downside risk proposed by Eppen et al. (1989) as the risk measure. Later, they (Barbaro and Bagajewicz, 2004b) extend their work by involving inventory and option contracts to hedge financial risk in the process planning.

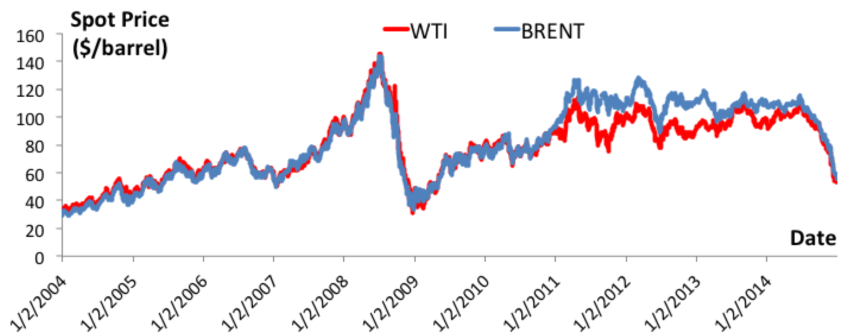

Figure 1 - Illustration of crude oil price from 2004 -2014.

Pongsakdi et al.(2006) also use financial risk as risk measure to study the refinery planning problem considering oil price and product demand uncertainty. Later, Park et al.(2009) extend the work by Pongsakdi et al.(2006), and analyze how spot contract, future contract and option contract influence the procurement decisions.

Similar to probability based financial risk, CVaR is another widely used risk measure. Carneiro et al.(2010) discuss the Brazil oil supply chain optimization problem with a two-stage stochastic model incorporating CVaR. Verderame and Floudas(2009) also use CVaR to address batch plant planning under demand, due time and amount uncertainty.

To our knowledge, the most relevant article is Barbaro and Bagajewicz(2004b). Our work extends their research by introducing future contract and call/put options as well as CVaR as the risk measure. Moreover, Sample Average Approximation (SAA) is applied to solve the problem. Besides, useful insights are drawn from the numerical experiments, which not only imply the benefits of the suggested approach, but also help managers to improve the procurement decision making process.

The remainder of the paper is organized as follows. Section 2 describes the problem in detail. And Section 3 formulates the problem as one stage stochastic programming model, and sampling average approximation method is applied to tackle the resulting MIP model. Numerical experiments are conducted in Section 4, which demonstrate the benefits of the proposed integrated hedging strategy and provides useful insights. Finally, we summarize the research and discuss future research directions.

Problem Statement

The problem addressed in this article can be described as follows. We are given a refining process shown in Figure 2 (Kendrick et al., 1991), and also a set of crude oil that can be procured and refined both from spot market and through financial contracts. For each crude oil c, the spot price in period t is given as sc,t which is stochastic. The planning horizon is divided to discrete t intervals. At the beginning of each period, managers should make decisions about spot trading and contract trading. We assume spot trading is done immediately, and all the demand for end product must be satisfied.

In addition, the planning procedures also benefit from using financial derivatives as suggested by Barbaro and Bagajewicz (2004b) and Park et al.(2009). In this research, we consider future contract, put option and call option. Moreover, we assume that all the future contract is paid by oil delivery, while the option contract is transacted without oil delivery. We also assume the time lag between purchase and payment of the three types of contract is one-period as suggested by Park et al. (2009).

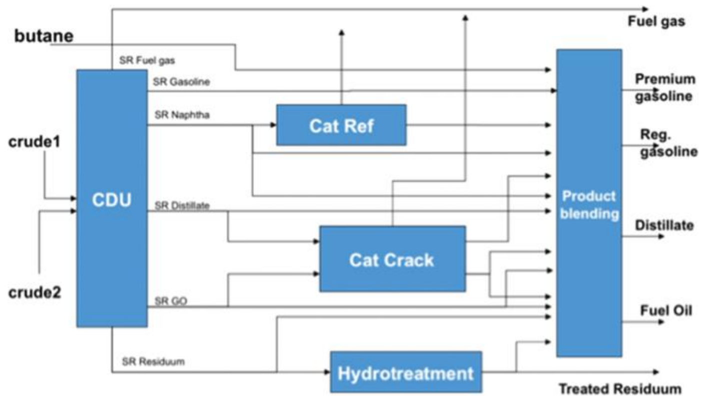

Figure 2 - Complex refinery configuration.

With the objective to minimize the CVaR associated with the total costs, the decision is to determine which crude oil to procure for spot market and the procurement quantity, and also the quantity of each contract to purchase at each time period. To tackle this problem we propose a one-stage stochastic programming model, and stochastic spot price is going to be handled through SAA method.

Formulation

The problem is formulated as one stage stochastic programming model that takes into account the material flow conversation, inventory, unit capacity, product property, end product demand, availability of crude oil and financial derivatives. We start with notation used in this paper.

Subscripts and Sets.

$c \in C$ Crude oil type
$d \in D$ Derivative type
$k \in K$ Refining unit
$l \in L$ Refining intermediates
$p \in P$ Set of end product
$r \in R$ Set of product property
$t \in T$ Planning time period

Decision Variables.

$BC_{c,t}$ Procurement quantity of crude c in period t
$FC_{c,t}$ Refining quantity of crude c in period t
$Qder_{c,d,t}$ Quantity of derivative d for crude c in period t
$PE_{p,t}$ Quantity of end product p in period t
$Inv_{c,t}$ Inventory level of crude c at the end of period t
$ST_{c,l,k,t}$ Stream l outlet from unit k for crude c in period t
$ST_{c,p,t}$ Stream of end production from crude c in period t
$CVaR_{\alpha}$ CVaR value at risk level α
q_{α} VaR value at quantile α

$Pr_{r,l,k,c,t}$ Property r in the outlet stream l from unit k of crude c in period t
$Zder_{c,d,t}$ Binary indicator for signing derivative d for crude c in period t

Parameters.

$s_{c,t}$ Spot price of crude c in period t with distribution S and support Ω
$sc_{c,d,t}$ Setup cost for contract d of crude c in period t
$sp_{c,d,t}$ Strike price of derivative d concerning crude oil c in t
$ProdCost_k$ Unit production cost for production facility k
$AvailC_{c,t}$ Supply upper bound on oil c in period t
$AvailD_{c,d,t}$ Supply upper bound on derivative d associated with oil c in period t
$Demand_{p,t}$ Demand for end product p in period t
h_c Holding cost of crude c
$Capacity_k$ Capacity limit for unit k
$PRU_{p,r,t}$ Upper bound on property r in end product p
$PRL_{p,r,t}$ Upper bound on property r in end product p
$\beta_{c,l,k,t}$ Yield ratio of outlet stream from input stream l in unit k of crude c

Next, we give the expression of the constraints to formulate the problem.

Crude oil inventory conservation & capacity. In the multiperiod framework, the inventory level of crude oil c at the beginning of each period t + 1, which is represented as $Inv_{c,t+1}$, is given by,

$$Inv_{c,t+1} = Inv_{c,t} + BC_{c,t} - FC_{c,t} + Qder_{c,future,t-1}, \qquad \forall c \in C, t \in T \tag{1}$$

where $BC_{c,t}$, $FC_{c,t}$ and $Qder_{c,future,t-1}$ denote procurement quantity, refining quantity and future contract payment quantity of crude oil c, respectively. Note that we assume one period time lag between contract purchase and payment, which means the contract purchased at t - 1 is exercised at t, and only future contract is paid by crude oil delivery.

Moreover, short selling is not allowed so that all the inventory level of crude oil must be greater than 0, which is expressed by

$$0 \leq Inv_{c,t+1} \leq Cap, \qquad \forall c \in C, t \in T \tag{2}$$

Production unit capacity. Total quantity of outlet streams from unit k, which represents the production quantity, is bounded by the unit capacity as

$$\textstyle\sum_{c\in C} \sum_{l\in L} ST_{c,l,k,t} \leq Capacity_k. \tag{3}$$

And the outlet stream is determined by the yield relationship given by

$$ST_{c,\hat{l},k,t} = \beta_{c,\hat{l},k,t} ST_{c,l,k,t}, \tag{4}$$

where $\beta_{c,\hat{l},k,t}$ is the yield ratio of outlet stream $\hat{l}$ from the input stream j in unit k.

Product property. The quality of end product is also considered, which is expressed by forcing the net property of each outlet stream lies between the lower bound and the upper bound.

Note that $\sum_{l \in L} \sum_{k \in K} Pr_{r,l,k,c,t} ST_{c,l,k,t}$ equals to the net properties of type r from all the outlet stream. Then we describe product property constraints as follows.

$$ST_{c,p,t} = \sum_{l \in L} ST_{c,l,k,t}\,, k \text{ are blending units.} \tag{5}$$

$$ST_{c,p,t} PRU_{p,r,t} \geq \sum_{l \in L} \sum_{k \in K} Pr_{r,l,k,c,t} ST_{c,l,k,t}. \tag{6}$$

$$ST_{c,p,t} PRL_{p,r,t} \geq \sum_{l \in L} \sum_{k \in K} Pr_{r,l,k,c,t} ST_{c,l,k,t}. \tag{7}$$

End product demand. Total production quantity of end product p is calculated by the summation of all the outlet streams of product p.

$$PE_{p,t} = \sum_{c \in C} \in ST_{c,p,t}\,, \ \forall p \in P, t \in T. \tag{8}$$

All the demand for end product p must be satisfied, that is,

$$PE_{p,t} \geq Demand_{p,t}, \qquad \forall p \in P, t \in T. \tag{9}$$

Availability on crude oil and derivatives. The procurement quantity of crude oil c in period t is bounded by the availability, which is given by,

$$BC_{c,t} \leq AvailC_{c,t}, \qquad \forall c \in C, t \in T. \tag{10}$$

Meanwhile the purchase amount of financial contracts also have upper bound limitation as,

$$0 \leq Qder_{c,d,t} \leq AvailD_{c,d,t} Zder_{c,d,t}, \qquad \forall c \in C, d \in D, t \in T. \tag{11}$$

Objective Function

In this research CVaR is selected as the risk measure. First we give the expression of total cost, which consists spot procuring cost, payoffs of financial derivatives, production cost, and holding cost of crude oil. Define

Cost as the total costs;
$Cost_t^s$ as spot procuring cost in period t;
$Cost_t^d$ as cost associated with financial derivatives in period t;
$Cost_t^p$ (Z,Q) as production cost in period t;
$Cost_t^h$ as holding cost in period t;
Then the total cost is given by

$$Cost = \sum_{t \in T} Cost_t^s + Cost_t^d + Cost_t^p + Cost_t^h.$$

and hence, the expected total cost is expressed as $E_{s \in S}[Cost]$.

The crude oil procurement cost in each period is $Cost_t^s = \sum_{c \in C} BC_{c,t} s_{c,t}$.

Since the future contract must be paid with crude oil delivery, the cost associated with the future contract equals to the contract setup cost $Zder_{c,d,t}sc_{c,d}$plus strike price multiplied by the contract quantity. Note that the strike price for future contract is the spot price when signing the contract, that is $s_{c,t-1}$.

As for call option, if spot price$s_{c,t}$ is greater than the strike price $sp_{c,d,t-1}$ then the contract will introduce benefit as $(s_{c,t} - sp_{c,d,t-1})Qder_{c,d,t-1}$. Otherwise because owners of this call option have the right to give up this contract, the payoff of this contract is zero. So the cost associated with such call option is the contract setup cost minus the payoffs. The calculation of put option is similar to the call option. Thus, the cost associated with three types of contract is given by,

$$Cost_t^d = \begin{cases} \sum_{c\in C}\{Zder_{c,d,t}sc_{c,d} + s_{c,t-1}Qder_{c,d,t-1}\}, & d = future \\ \sum_{c\in C}\{Zder_{c,d,t}sc_{c,d} - (s_{c,t} - sp_{c,d,t-1})^+Qder_{c,d,t-1}\}, & d = call\ option, \\ \sum_{c\in C}\{Zder_{c,d,t}sc_{c,d} - (sp_{c,d,t-1} - s_{c,t})^+Qder_{c,d,t-1}\}, & d = put\ option \end{cases}$$

where the operator $(x)^+ = x$ if $x \geq 0$, and = 0 otherwise.

The production cost is expressed by,

$$Cost_t^p = \sum_{k\in K}\{ProdCost_k \sum_{c\in C}\sum_{l\in L} ST_{c,l,k,t}\}.$$

The inventory holding cost is given by,

$$Cost_t^h = \sum_{c\in C} Inv_{c,t}h_c.$$

According to Pflug (2000), CVaR is calculated as

$$CVaR_\alpha = inf_{q_\alpha \in R}\left\{q_\alpha + \frac{E_{s\in S}[Cost - q_\alpha]}{1-\alpha}\right\}. \tag{12}$$

Note that α is the confidence level and is set to 95%, while qα is the associated α level Value-at-Risk. By minimizing the right hand side of equation (12), CVaR as well as VaR can be obtained.

Hence the objective function is to minimize CVaR value as

$$\min CVaR_\alpha \tag{13}$$

The entire model is then given by the MIP formulation with objective as (13) subject to the constraints (1)-(11).

SAA Solution Method

The well known SAA method is widely used for dealing with stochastic programming. By generating a random sample $\{s_1, s_2, \ldots, s_N\}$ of the stochastic price S, we can solve the deterministic approximation of objectives (13) as

$$min_{q_\alpha \in R}\{q_\alpha + \frac{1}{N}\sum_{i=1}^{N}\frac{1}{1-\alpha}(Cost_{s_i} - q_\alpha)^+\}, \tag{14}$$

where N is the pre-defined sampling size, and $Cost_{s_i}$ is the total cost associated with oil price scenario s_i.

Equation (14) is also used as the estimator suggested by Trindade et al. (2007). Mostly important they prove (Trindade et al., 2007) the strong consistency and asymptotic normality of such estimator, which indicate the convergence property of our proposed method.

In this research the oil prices are assumed to follow the Geometric Brownian Motion (GBM), which is also used in the previous research such as Al-Harthy (2007); Aspen (2011); Liu et al. (2012). We illustrate the one sample of the crude oil price in Figure 3.

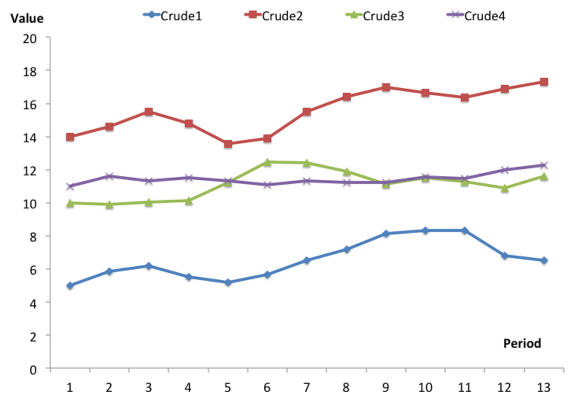

Figure 3 - Illustration of GBM oil price sample.

Numerical Experiments

In this section we present results for numerical experiments. The impact of inventory, financial derivatives, and crude oil price behavior are studied in detail, which provide useful insights for managers to deal with crude oil procurement decision.

In the following experiments we consider a planning horizon of 3 months, subdivided into 12 periods with 1 week per time period. 4 types of crude oils are considered. Detail data are available upon request. All of the tested models are implemented with GAMS 22.4 in Core i7 2.93 GHz CPU and RAM 4.0 GB. The optimal tolerances for all the instances are set to be 0.

Impact of Inventory Hedging

As a sensitivity analysis, the inventory upper bound is varied from 100 to 350 with step size 50. The cost compositions under different cases are drawn in the primary axis (left axis), and the corresponding CVaR values are plotted in the secondary axis (right axis) in Figure 4.

We can see that the impact of inventory is also significant, which provides about 15% total costs reduction and 10% CVaR reduction. This result will help managers to realize that expanding inventory upper bound will lead to better risk management as well as lower total costs.

Impact of Financial Derivatives

To study the impact of financial derivatives quantitatively, four cases are considered: A. the model without contract; B. model considering contract but without risk management; C. model with CVaR as constraints; and D. the model proposed in this research. The results are shown in Table 1.

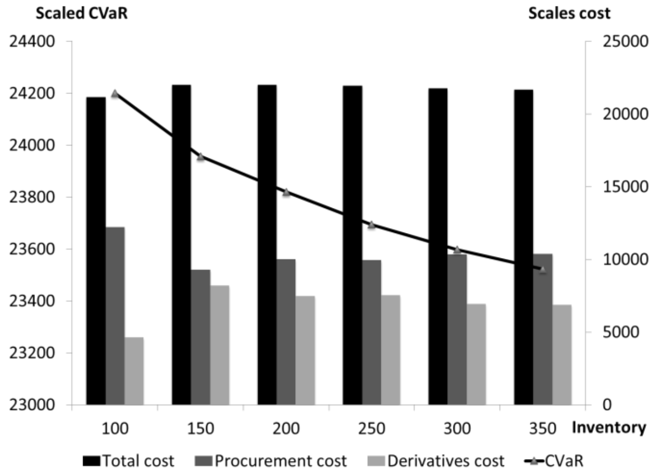

Figure 4 - Sensitivity analysis of inventory on total cost composition and CVaR.

By comparing the case considering contract but without risk management and the last case, we can see that nearly 10% enhancement in CVaR is observed at the sacrifice of total costs increase of 3%. The comparison between the first case and the second case shows an improvement more than 11% in total costs, verifying the benefit of financial derivatives.

Table 1- Benefits from financial hedging.

Case	Total Cost	Procuring Cost	Derivatives Cost	CVaR	VaR
A	20173	15428	0	22698	21905
B	18094	9583	4210	21458	20808
C	18596	8405	5904	20137	19976
D	18397	10018	4038	21259	20065

Another important observation is that, by comparison the case with CVaR as objectives and the case with CVaR as constraint, total cost reduces less than 1% while CVaR increases about 5%, which helps to explain why CVaR is used as the objectives not constraints in this research.

Impact of Price Behavior

Another important issue is to study how price distribution influence the results and ultimately influence procurement decisions.

First, we conduct 2 level full-factorial experiment to illustrate the impact of price volatility parameter σ. CVaR is used as response in this experiment, and the volatility of distribution of crude oil C, which is represented by σc, has two levels, that is 140% or 60% of original value.

Table 2 - ANOVA for impact of volatility on CVaR.

Source	SS	P
$\sigma 1$	557	0.01
$\sigma 2$	628	0.01
$\sigma 3$	499	0.03
$\sigma 4$	675	0.01
Interaction	879	0.00
Residual Errors	272	
Total	3509	

The ANOVA results are listed in Table 2, which shows that the impact of price volatility is significant under 95% confidence level. Moreover, volatility positively influence the CVaR value, which indicates that the scenario with lower price volatility is preferred.

Despite of volatility, the distribution covariance is another very important issue of interest. Next, a comparison study is conducted to show the impact of price distribution covariance. The covariance is set to five levels, two of which are positively correlated (elements in the up triangle of the covariant matrix Σ are drawn from U(0,1)), tow of which are negatively correlated (elements in the up triangle of Σ are drawn from -*U*(0,1)), and one case is independent (elements of Σ equal to 0). The corresponding CVaR and total cost are plotted in Figure 5.

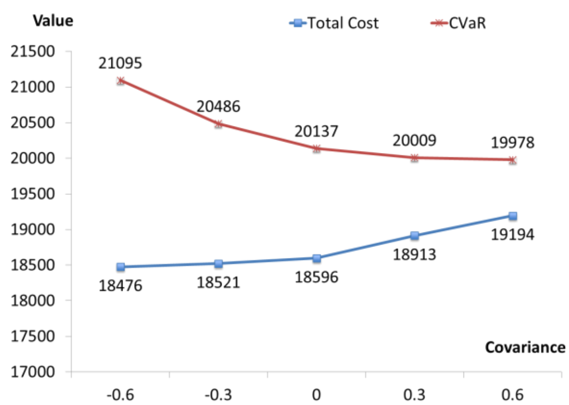

Figure 5 - Impact of covariance on CVaR and total cost.

As can be seen, the cases with negatively correlated covariance provide solution with higher total cost but lower CVaR, while the cases with positively correlated covariance show the opposite results. This conclusion illustrates the trade-offs between total cost and risk management for managers.

Conclusion & Discussion

The paper presents an integrated operational and financial hedging strategy on procurement risk management concerning oil price uncertainty. Inventory and three financial derivatives which are future, put option and call option, are considered. Meanwhile CVaR is used as the risk measure and the SAA method is applied to solve the proposed one stage stochastic programming model. Numerical studies verify the benefits of all the strategy, and some useful comparison studies also provide managerial insights. Moreover, experiments on crude oil's price behavior imply that large price volatility lead to worse risk management performance, and negatively correlated oil prices are preferred because managers can construct a less risky oil portfolio from those oils with negatively correlated price.

As future research directions, it is interesting to extend the operational hedging strategy like blending strategy and pricing of end product. Meanwhile since this research considers three basic derivatives, discussing more complex while useful derivatives such as swaption will provide better procurement decision support. Moreover, there are other uncertainties faced with industrial managers such as availability of crude oil and transportations, which also need careful and further discussion.

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