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Chapter 1
A Bayesian Learning Approach for Making Procurement Policies Under Price Uncertainty

Zhi-xue Xie and Li Zheng

Abstract In this paper we consider a procurement problem under purchase price uncertainty, which is the case encountered by companies who purchase from spot markets with fluctuating prices. We develop a procurement model by introducing the dynamics of information revelation via Bayesian learning, derive its optimal solution and identify some thresholds to improve purchase timing decisions. Using historical spot price data of crudes oils, we verify the effectiveness of proposed policies compared to the current policy of Chinese oil refineries, and find the Bayesian learning model does perform well—billions of dollars could be saved over the past several years.

Keywords Bayesian · Price uncertainty · Procurement management · Purchase timing

1.1 Introduction

Making procurement policies turns to be more and more challenging for manufacturers dealing with commodities with violent price fluctuations, such as agricultural products, precious metals, mineral and energy resources. The timing decision is a particularly hard choice for them; procurement made too early will cause unnecessary inventory holding costs and miss the opportunity to purchase at a possibly lower price in the future, while it made too late may squander the chance to purchase at an earlier cheaper price.

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This research is motivated by crude oil procurement decision-making problems faced by an oil refinery in China Petroleum & Chemical Corporation. Under current policy of importing crude oils from international market, the refinery is highly exposed to huge price risk, in that its orders are just evenly distributed along the planning horizons so the settlement prices are generally dependent on the spot prices during corresponding periods; it is actually playing as a speculator in the international crude oil market. Given the fact that crude oil procurement cost accounts for over 85 % of the overall costs of an oil refinery Jiang (2010); Yu and Fang (2005), obliviously this is not a pleasant situation.

Total cost of crude oil procurement consists of four components, the spot price of some marker crude, an adjustment factor, freight, and miscellaneous charges, but the contributions of the latter three are relatively small and less important compared to high and volatile crude spot prices (we will discuss about the freight issue a little more in the modeling part); hence it is reasonable for this research to focus on the oil price. There are two kinds of contracts in physical transactions, term contract and spot contract. The term contract in crude procurement practice, however, is quite different from commonly known long-term fixed-price contract in other supply chains; the unit price of purchased crude oil under a term contract is determined on the basis of spot prices in a certain period around its lifting time rather than settled at the time of ordering, the same as under a spot contract. Focused on the spot price issue, we do not distinguish between these two types of contracts hereafter.

Oil prices have historically tended to be notoriously difficult to predict, resulted from a combination of fundamentals and market behaviors, financial factors such as oil futures prices and exchange rates, as well as economic events, military affairs and politics. This complexity in price uncertainty, together with the fact crude oil is the most influential commodity, makes our study more significant. And this research, though aimed at Chinese refineries, provides potential benefits to world-wide manufactures in commodity industries that bear some resemblance with it.

The remainder of this paper is organized as follows. In Sect. 1.2, the relevant literature is reviewed. The procurement problem is modeled in Sect. 1.3, and the analytical solutions are provided. Next in Sect. 1.4, real-world data are used to test the effectiveness of proposed decision policies. Conclusions are given in Sect. 1.5 with some important directions for future research.

1.2 Literature Review

There are two lines of literature related to this research, procurement models under purchase price uncertainty, and operations management studies involving information updating.

1.2.1 Procurement Under Purchase Price Uncertainty

As many as procurement and inventory management researches in operations management and supply chain management literature, they generally assume constant or known purchase prices and work on fulfilling stochastic demands; studies on stochastic purchase price uncertainty are limited. Fabian et al. (1959) is probably the first inventory research that considers price uncertainty under stochastic demand and Golabi (1985) addresses a problem with random ordering prices and deterministic demands; but they both assume known and independent distribution function for future prices, which are not applicable to commodity prices. Kalymon (1971) studies an inventory model in which the purchase price follows a Markovian process, (Yi J, Scheller-Wolf A Dual sourcing from a regular supplier and a spot Market. unpublished) considers a multiple sourcing problem with a fixed-price supply mode and a stochastic price mode, and lately Berling and Martínez-de-Albéniz (2011) develops an effective procedure to characterize optimal base-stock levels based on earlier structural results. A work closely related to ours is Li and Kouvelis (1999) because we assume the same demands pattern and price processes as one of their cases does. However, former inventory control models all assume spot price value becomes known before ordering decision is made to obtain some price-dependent policies. Our study is unique in modeling the difference between spot price at the time of ordering and that at purchasing due to industrial practices, and we also incorporate information revelation dynamics within the procurement problem.

1.2.2 Information Update in Operations Management

Several authors have studied information acquisition and forecast updates in procurement problems. (Gaur V, Seshadri S, Subrahmanyam MG Optimal timing of inventory decisions with price uncertainty, unpublished) Considers an inventory timing decision with forecasts updating for correlated demand and selling price, but deterministic purchase cost. Gurnani and Tang (1999) proposes a two period procurement model for seasonal product with uncertain demand and purchase price, but only the demand is updated upon market signals between two selling instants. (Secomandi N, Kekre S Commodity procurement with demand forecast and forward price updates, unpublished) Derives the optimal procurement policy under correlated demand forecast and forward price updates in the presence of forward and spot markets. The existing literature generally focuses on the trade-off between more accurate forecasts on demand and (potentially) higher costs, while our problem is featured by deterministic demands and independent uncertain purchase prices.

Bayesian method is not popular in procurement models, but has been extensively used in inventory models [Scarf (1959); Karlin (1960); Azoury (1985)].

However, they are all about uncertain demands which distribution is periodically updated based on newly obtained demand observations. Inspiringly, Miller et al. (2005) incorporates Bayesian learning within a process design and capacity planning problem and identifies a threshold to improve decision-making; we adopt their framework and apply it to our procurement problem.

1.3 The Procurement Models

Consider an oil refinery faced with multiple dynamic but deterministic demands for crude oils, which must be met and will be purchased at spot prices, and amounts arrived before demanded trigger inventory holding costs. The assumption of known demands pattern is realistic in this problem based on three reasons. First, various kinds of oil products could serve several purposes such as generating power, providing energies to automobiles and airplanes, etc., consequently the overall oil demands arising from both life and industry do not fluctuate violently, especially compared with the volatility of crude oil price. Second, since there are industry regulations in Chinese oil markets to ensure relatively steady supply of oil products, major refineries usually report their production plans yearly to the administration and stick to them after being approved. Third, process industries such as oil refining, characterized by continuous production process that couldn't afford to be disturbed too much, generally operate according to the determined production plans out of economic considerations.

1.3.1 Basics of Cost Modeling

As researchers studying on the spot price of commodities did, we assume that the spot price of each unit (e.g., barrel) of the crude oil, S_t, follows a geometric Brownian motion with drift μ and volatility σ

$$dS_t/S_t = \mu \cdot dt + \sigma \cdot dW_t, \tag{1.1}$$

where W_t is a standard Weiner process. Note the point in time that matters is when payment is made, not when order is placed. The terms on valuation time periods are negotiable in practice, so for simplicity, the purchasing price is represented by the spot price at delivery in following derivations and by the average of spot prices during the lead time in empirical studies.

As inventory holding cost consists of cost of capital, cost of storage, insurance, breakage, and many other items, among which cost of capital is the most significant component, we assume the inventory holding cost (per unit per time) is charged at a fixed proportion, $0 < \theta < 1$, to the corresponding purchasing cost. That is,

$$h_t = \theta \cdot S_t. \tag{1.2}$$

In our problem, modeling in this way is more reasonable than commonly used stationary or independent setting, because the cost of capital is particularly high for the oil industry, which is capital-intensive.

What's more, it is realistic to assume a lead time, say, one period, i.e., the ordered quantity in current period will be delivered and paid in next period. Such a setting also emphasizes the difference between the spot price observed when the crude oils are ordered and the price to pay when they are received. Assume the time length of one period is Δt.

1.3.2 Purchasing Timing Problem

The refinery's decision is to determine when and how many units to purchase each time to minimize the total expected costs over the planning horizon, in other words, the refinery would behave risk-neutrally when making procurement decisions. Risk-aversion modeling can be found in Martínez-de-Albéniz and Simchi-Levi (2006), and it could be incorporated in the model by adjusting the drift term.

In this procurement problem, the refinery has a series of choices on ordering timings for each quantity demanded and every single period in the planning horizon is an option. Say there are n demands in the planning horizon, because supply lead times are fixed, order i will always be used to serve the ith demand, which arrival time and quantity are denoted by T_i and D_i. We want to find an optimal series of arrival times of each ordered quantity, denoting the ith order's delivery time as t_i (thus its ordering time is $t_i - \Delta t$), to obtain a minimization as

$$\min_{t_i} E\{\sum_{i=1}^{n} e^{-rt_i}[D_i \cdot S_{t_i} + D_i \cdot h_{t_i}(T_i - t_i)]\}, \tag{1.3}$$

where r is an appropriate discount rate. The procurement problem can be solved independently, as shown in Li and Kouvelis (1999) and Miller et al. (2005), for each demand as

$$\min_{t_i} E\{e^{-rt_i} D_i \cdot S_{t_i}[1 + \theta(T_i - t_i)]\}. \tag{1.4}$$

1.3.3 A Passive Decision Model

Let $F(t, S_t)$ be the minimum expected discounted total cost if the current time is t, the current unit price is S_t, and the firm has not made the purchase before. The Bellman equation is

$$F(t,S_t)=\min\left\{e^{-r(t+\Delta t)}\cdot D\cdot E[S_{t+\Delta t}|S_t]\cdot[1+\theta\cdot(T-t-\Delta t)],\ E[F(t+\Delta t,S_{t+\Delta t})|S_t]\right\}, \tag{1.5}$$

where the first and second terms in braces on the right side of Eq. (1.5) are the "payoff" functions of termination and continuation, respectively. The objective function is F (0, S_0) where S_0 is the spot price of the material at time 0; the boundary condition is

$$F(T-\Delta t,S_{T-\Delta t})=e^{-rT}\cdot D\cdot E[S_T|S_{T-\Delta t}]. \tag{1.6}$$

Now we are ready to derive the optimal timing decision, and a passive decision rule can be obtained as follows (we will come back to the meaning of "passive" later).

Property 1 *The optimal timing decision is to order at time 0 (to purchase at time Δt) if*

$$e^{(\mu-r)(T-\Delta t)}-\theta(T-\Delta t)-1>0, \tag{1.7}$$

and to order at time $T-\Delta t$ (to purchase at time T) otherwise. Accordingly, the optimal value of objective function (minimum cost) can be derived in a straightforward way.

Note that the optimal purchasing decision for the stochastic case is the same as if the price volatility is zero, which makes sense since we are optimizing on the expectation level where the stochastic problem reduces to have the similar property as in the deterministic case. Also as interpreted by Li and Kouvelis (1999), because observing the price path of a geometric Brownian motion gives us no new information about the distribution of price changes of the material in the future, the optimal timing for the firm's purchase can be determined at time 0.

However, this "expected scenario" analysis makes an implicit assumption that the decision-maker acts passively following the decision made at the beginning of planning horizon, which can be problematic in the actual marketplace characterized by change and uncertainty, because the realization of spot prices will probably be quite different from what the decision-maker expected initially. Therefore, the passive decision models works well only when the price trend remains the same along the planning horizon, which situation is rare for crude oils in this decade.

Note the drift μ at time 0 is actually what we have estimated without any future spot prices; then a natural thought is, if some future price realizations suggest a change in price trend, we don't have to stick to the former decisions. Such flexibility of management serves as the central idea of real options literature. To address this passive management problem, we introduce Bayesian learning to actively make use of new information; that is the "active" decision model.

1.3.4 An Active Decision Model

Suppose we obtain at time 0 an estimate of future spot price that follows a log-normal distribution; its logarithm is normally distributed with an unknown mean $\tilde{\mu}$ and a known variance σ. We may regard $\tilde{\mu}$ as a random variable and learn more about it under Bayes rule. Presume the prior belief is normally distributed as N (μ_{00}, σ_{00}). Spot prices between period 0 and period 1 are observed as time evolves from 0 to Δt, denoted by s_{1k}. There could be more than one price realizations ($k > 1$) between consecutive decision points in time, because the spot price process evolves in a continuous pattern from which we can obtain several discrete realizations; for instance, we make ordering decisions per month while obtain price information per day. Then, as shown in, (Fink D A compendium of conjugate priors, unpublished) the posterior distribution of $\tilde{\mu}$ is also normal with mean and standard variance

$$\begin{gathered} \mu_{01} = \alpha_1 \mu_{00} + (1 - \alpha_1) s_1,\ \sigma_{01} = \sqrt{\alpha_1}\sigma_{00} \\ \alpha_1 = \sigma^2 / (\sigma^2 + k\sigma_{00}^2), \end{gathered} \tag{1.8}$$

where s_1 is the mean statistic of logarithms of spot price data.

Now we are most concerned with whether there is any opportunity to improve the passive decision made at time 0 when additional information is gathered.

Property 2 *If the purchasing decision at time 0 is to order at time $T-\Delta t$, then at period 1 the threshold of the newly gathered information about price realizations that reverses the prior decision is*

$$s_1^* = \frac{r + \frac{\ln[\theta(T-2\Delta t)+1]}{T-2\Delta t} - \frac{\sigma^2}{2} - \alpha_1 \mu_{00}}{1 - \alpha_1} \tag{1.9}$$

where $T-2\Delta t > 0$. In other words, we should advance the ordering time to now as long as $s_1 > s_1^*$, and hold on to the prior decision otherwise.

If the prior decision remains unchanged at period 1, then after new information is obtained at later periods, similar procedure should be followed. And it is straightforward to extend Property 2 to later periods.

1.4 Case Applications

Now we apply the proposed models to the procurement problems faced by Chinese refineries, and the empirical studies are based on real-world data in crude oil spot market. The benchmark model is the current policies of Chinese refineries, under which the orders are almost evenly distributed along the planning horizons.

1.4.1 Data and Procedure

Our data set comes from public data source (Energy Information Administration) and consists of daily spot prices (USD per barrel) of WTI from 1986/1/2 to 2011/6/30 and those of Brent from 1988/1/4 to 2011/6/30. As for the quantity of crude oils China has imported from the international market, there are yearly volume data from 1994 to 2009, summing up to approximately 10.165 billion barrels.

We set half a month as the length of one period, which is also the length of lead time and decision making interval, and two months (four periods) as the length of one planning horizon. Taking case "demand for WTI at 2008/4/30" as an example, a typical data processing procedure is as follows:

(1) Set 2008/3/1 as time 0, 2008/4/30 as time T ($N = 4$), target demand to be served equals to 1; annualized risk-free rate equals to 3 %, which is approximately the one-year Treasury bond rate; annualized cost of capital as percentage to occupied capital equals to 36 %, which is relatively high because the oil industry is capital-intensive, as emphasized before.
(2) Use historical data, WTI's spot prices from 2008/1/1 to 2008/2/29, to estimate μ_{00} and σ at time 0; here we estimate from data of the past two months because we want to make decision for future two months. Make passive decision according to Property 1.
(3) For period 1 to $N-1$, if the order has not been placed before, consider spot prices data in each month as additional information; calculate parameters and statistics to make active decision according to Property 2.
(4) Use real-world price data to statistically assess the effectiveness of proposed decision models compared to the benchmark, in which the costs are calculated by taking average of the costs along the planning horizons.

1.4.2 Model Assessment

Faced with spot prices data from 1986/1988 to 2011 and volume data from 1994 to 2009, we perform rough yet reasonable calculations for the total costs by multiplying average unit purchase cost over 24/26 years by aggregate quantities of 16 years. We compare the proposed models to the current policy, and the results are summarized in Table 1.1.

Table 1.1 Effectiveness of proposed models

Marker crude	Total procurement costs[a]		
	Current policy	Passive model	Active model
WTI	369.36	370.59	364.74
Brent	374.94	377.49	371.97

[a] In billions of US dollars

Surprisingly, the passive model costs more than the current policy, perhaps because the oil price trend in the real world changes so frequently so it's no good for the refinery to act passively following the decision made at the beginning of planning horizon. However, the active model did save a lot of money for the refinery. Note all the numbers are in billions of US dollars; although they are not accurate, improvements are still considerable.

1.5 Conclusion

In this paper, we develop procurement policies, particularly for Chinese oil refineries, under purchase price uncertainty. Faced with difference between spot price at the time of ordering and that at purchasing, we formulate a procurement model and derive its optimal solution; but the model seems to be problematic when price trend changes. To address this weakness, we then incorporate Bayesian learning within the decision making process and identify a threshold of newly observed spot prices to improve the procurement timing decisions. Finally, we empirically validate the effectiveness of these proposed policies using public spot prices data for WTI from 1986 to 2011 and Brent from 1988 to 2011. Now we come to the conclusions that the order should be made at time 0 as suggested by the passive model only if the decision-maker has enough evidences to believe the oil price will increase at a relatively high rate throughout the planning horizon, otherwise the active model is worth trying, which is practically effective under not too long planning horizons.

The intrinsic logic of the Bayesian approach is that the thought process of judging oil prices to be high or low is a natural Bayesian process: when you see a realized price, you may think it as in high or low level and guess it will go up or down in the future; when the next period comes, you will see whether your judgment is right. If you have some opportunity to revise former decisions, the chance of your making good decisions would be bigger. This is the basic idea of the active model, and it indeed works well as proved by real data. However, our procurement model needs extensions to deal with some more issues. One significant direction of expending the current problem is to include an inventory capacity according to the actual constraint, then the model will be more applicable under longer planning horizons. Another direction is to address the problems of optimal hedging portfolio and its interaction with operations management, because financial hedging may be taken into consideration by Chinese oil companies in the future.

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