Procurement Planning to Maintain Both Short-Term Adaptiveness and Long-Term Perspective

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ABSTRACT

We study the fuel procurement problem for electrical utilities under uncertain demand and market price. Long-term contractual supply commitments are made at a set price with fuel suppliers at the beginning of each year. Each month the procurement planner can use fuel from these contracts or purchase fuel at the current market price. We propose a two-phase heuristic to determine a procurement plan. In the first phase the minimum contract purchases for each month are determined at the beginning of the year. In the second phase, given the minimum contract purchases, the more detailed procurement decisions are determined at the beginning of each month with the most up-to-date information. We perform intensive computational experiments which show that the heuristic produces high quality solutions comparable to a rolling horizon stochastic programming heuristic, is easier to maintain and generalize, is computationally faster, and is robust to random fluctuations in demand requirements, spot market prices, and other sources of uncertainty.

1. Introduction

Procurement from outside suppliers is a capital-intensive decision that often accounts for a large portion of the total operating costs. This research is motivated by our experiences with the fuel procurement problem of a mid-size electrical utility in the Northeast. During 1994, the cost of fuel procurement for this utility was approximately $459 million or 32.5% of the company's total operating and maintenance costs. In other words, a mere 3% reduction in fuel procurement costs could save the utility in excess of $10 million dollars annually.

Traditionally, utilities have long-term contractual commitments for a percentage of their projected annual demand to assure a committed supply of fuel. The remaining demand is procured through monthly *spot market purchases*, i.e., purchases at the current market price. Single or multiple year supply contracts provide an uninterrupted supply at a pre-negotiated price; however, the utility is locked into procuring designated quantities (paying an “underlift” penalty for taking less than the minimum committed amount) and is locked into a price that is usually higher than the current market price. Spot market purchases are usually at lower prices and complete flexibility; however, are at risk for uncontrolled price increases or sharp decreases in supply. Development of a procurement strategy must take into consideration the dynamic nature of demand requirements and spot market prices. The procurement model must be able to both satisfy the pre-negotiated contract quantity commitments and take advantage of favorable spot market prices

In the utility industry annual procurement planning can be summarized as one of two basic approaches. In the first, "myopic," planning approach procurement decisions are not made until the last moment. This method allows the manager to take into account the most up-to-date demand and spot market prices' information. Nonetheless it often fails to take a long-term perspective to the overall procurement cost. The second procurement planning approach can be viewed as "static" planning. Prior to the beginning of each year, a detailed monthly procurement plan is determined. The strategic plan is typically developed with the objectives of minimizing total procurement cost over the planning horizon while meeting all contract commitments. The plan is devised based on demand forecasts and other presumptions derived from historical data. Although this approach does take a global point of view to the procurement strategy and ensures all contract commitments are satisfied, it does not provide the flexibility to factor up-to-date information into the procurement decisions. As a result, the utility has limited ability to take advantage of low spot market prices, or procuring larger quantities from contracted sources if spot market prices exhibit sudden increases, e.g., the harsh winter in 1993-94, or the United Mine Worker strike in 1992.

In order to minimize total procurement costs, the utility must have the flexibility to adapt their procurement strategies to changes in initial assumptions. A completely specified procurement plan, maybe optimal at the time it is generated, is extremely vulnerable to changes. On the other hand, some global planning is necessary to properly balance contract and spot market purchases over time. In this paper, we describe a decision model designed to address main practical issues of short term planning by incorporating the merit of both "static" and "dynamic" planning. More specifically, the method maintains a global view of the long-term (annual) procurement strategy while providing the flexibility for decision-makers to adapt the strategic plans to unforeseen demand and spot market price deviations (monthly).

Although much of the discussion in this paper focuses on fuel procurement for utility companies, much broader implications can be made for other related applications. For instance, most contracted procurement problems must address the trade-off between long-term reserved sources of supplies and short-term cost saving opportunities. Applications in non-procurement contexts are also likely. For instance, Brown and Lee (1997) described a similar problem in supply chain management where semiconductor manufacturers make long-term reservation of future capacity at subcontract foundries. The goal is to develop flexible contract agreements that maximize long-term savings while hedging against volatile market fluctuations in the short-term.

1.1 Related Literature

Quantitative treatments to the procurement planning problem appears quite sparse in the literature. A majority of the research deals with qualitative vendor evaluation schemes. This line of work will not be reviewed here. There are a few quantitative models exist in the literature that addresses lower level, detailed purchasing decisions. Anthony and Buffa (1977) suggested a transportation model for static "purchase scheduling" problem that determines a multi-period purchasing plan for a given planning horizon. More recently Kingsman (1986) proposed a model for commodity purchasing decisions taking into account prices fluctuations. Pan (1989) developed an LP model for contract selection that determines the number of suppliers to select and allocation of order quantity among the suppliers. Several researchers proposed mixed integer programming models for detailed purchasing decisions (c.f., Gaballa (1974), Narasimhan and Stoynoff (1986), and Bender et al. (1985)). Most of the above models are static by nature where all purchasing decisions are made *a priori* at a specific point in time and no recourse is allowed for uncertain events such as demand and price fluctuations. The research in inventory theory also addresses some aspect of procurement planning. In particular, review policies for multi-level inventory systems with stochastic demand capture the essence of some procurement decisions (see Axs@ter (1993) and Federgruen (1993) for an excellent review). However, generalized version of these models is very difficult to solve and remains to be an active research area.

The Contract Mix Model developed by the Electric Power Research Institute (EPRI 1989) addresses more practical issues in procurement planning. The focus of this model was on long-term fuel procurement decisions based on a cost analysis of pre-determined fuel contracting strategies. However, the model focuses on long-term contracting strategies rather procurement strategies. Sponsored by EPRI, Morris et al. (1987) developed a Utility Fuel Inventory Model (UFIM) to help electric utilities set long-term fuel inventory strategy. UFIM is an integrated decision tool based on Monte Carlo simulation. The model focuses on long term planning issues related to supply disruption, fuel burn uncertainty, emergency management and seasonality.

2. Problem Statement and The Two-Phase Optimization Model

In the fuel procurement problem, a set of *m* contracts is given which have been negotiated and are in effect for the current year. Each contract *i* specifies a unit price p_{ij} for each month *j*, a *minimum committed annual quantity* l_i and a *maximum allowable annual quantity* u_i. The decision-maker has the flexibility to procure any amount within the contract quantity range $[l_i, u_i]$. Spot market purchases are also considered as a source of fuel supplies to meet the monthly demand requirements. Forecasted unit spot market prices s_j for each month $j=1,...,12$, and forecasted monthly demand requirements d_j are given at the beginning of the year. The actual spot market price $\underline{s}_j$ is available at the beginning of each month, while the actual demand $\underline{d}_j$ is known at the end of each month. There is an inventory holding cost *h*, for each unit of fuel carried over for each month. Moreover, the utility maintains a safety stockpile inventory *I* that could be used during the month to meet certain demand shortfalls, but it must be replenished to its original level at the beginning of each month. The objective of procurement planning is to determine the exact fuel purchasing quantity no later than the beginning of each month so as to minimize the ultimate annual fuel cost, while ensuring all demand requirements and contract quantity commitments are satisfied. As discussed in Bonser, Wu and Storer (1996), if the statistical distribution of demand requirements and spot prices is known *a priori*, this problem can be formulated as a multi-stage stochastic program as follows:

w = a particular instance of demand and spot price scenario over T periods (12 months)
Ω = the set of all possible scenarios
x_{ij}^{w} = amount to be purchased from contract i in month j under scenario w
sp_{j}^{w} = amount to be purchased from the spot market in month j under scenario w
P_w = probability associated with scenario w
s_{j}^{w} = spot market price in month j under scenario w
d_{j}^{w} = demand in month j under secnario w
cc = inventory carrying cost

$$\sum_{j=1}^{T}\sum_{w\in\Omega}P_w\,(p_{ij}x_{ij}^{w} + s_{j}^{w}sp_{j}^{w} + cc\cdot C_{j}^{w}) + \sum_{w\in\Omega}P_w\cdot s_{T}^{w}\,(I - C_{j}^{w})$$

$s.t.$

$$C_{j}^{w} = \sum_{i=1}^{n}x_{ij}^{w} + C_{j-1}^{w} + sp_{j}^{w} - d_{j}^{w} \qquad j = 2,\ldots,T,\forall w$$

$$l_i \le \sum_{j=1}^{T}x_{ij}^{w} \le u_i \qquad \forall w,i$$

$$\sum_{i=1}^{n}x_{ij}^{w} + sp_{j}^{w} + C_{j-1}^{w} \ge I + d_{j}^{w} \qquad j = 2,\ldots,T,\forall w$$

$$x_{ij}^{w}, sp_{j}^{w} \ge 0 \qquad \forall i,j,w$$

The stochastic program minimizes expected costs over all possible demand and spot price scenarios in T=12 periods. The first set of constraints defines the inventory carrying over from period *j-1* to *j*. The second set of constraint states that the lower and upper limits specified by each contract must be satisfied. The third set of constraints indicates that the safety stock inventory *I* must be replenished and the monthly demand must be satisfied. The above stochastic program has two major difficulties: first, it assume that the probability of each demand and spot price scenario is known *a priori,* which is restrictive and somewhat impractical. Second, the number of scenarios suffers combinatorial explosion as we try to consider "reasonable" demand and spot price fluctuations. Consequently, solving a twelve-stage (one for each month) stochastic program with uncertain demands and spot prices would be computationally infeasible for a realistic-size fuel procurement problem. A computational feasible heuristic is necessary to tackle this problem. Bonser, Wu and Storer (1996) proposed a computational heuristic for the stochastic program. They first simplify the model to consider only demand uncertainty and they limit the model to k-stages, where k is determined by the amount of computing power available (e.g., k=3 in their testing). These shorter-range stochastic programs are then resolved in a monthly basis using a rolling-horizon scheme.

In this paper, we propose a two-phase heuristic for this problem. To overcome the inherit computational burden, the heuristic simplifies *a priori* planning (*Phase I)* by focusing only decisions relevant to the long term interests of the procurement, while detailed procurement planning (*Phase II)* is made dynamically when more accurate demand and spot price information becomes available. We summarize this two-phase scheme in Figure 1.

Phase I- Contract Allocation

Each contract i is committed at least x_{ij} in month j

(decision made in January)

In the following we describe the two-phase scheme in detail. In the computational experiments, we evaluate the proposed scheme using the above *stochastic programming heuristic* as a benchmark.

2.1 Phase I: Contract Allocation

Phase I is a contract allocation model to be solved *a priori* at the beginning of the planning year. The model can be viewed as a "preprocessor" for the detailed procurement planning linear programme (in Phase II). It allocates the *minimum annual committed quantity* stipulated by the current set of contracts to each of the next twelve months such that all contract commitments are met. Since the minimum contract purchases only satisfy a portion of the monthly demand, the remainder of the demand is satisfied by potential *spot market purchases* hedging against the *residual quantity* (i.e., the difference between *maximum allowable quantity* and c*ommitted quantity*) of each contract.

To simplify the analysis, we assume that the underlift penalty is always greater than the marginal difference between contract and spot market purchases. This in term takes away the incentive for the utility to violate the minimum quantity commitment. To ensure that the *minimum committed annual quantity* l

Thus, the contract allocation problem may be posed as follows: we are given m contracts ($i=1,...,m$) that each has a known *minimum committed annual quantity* l_i and maximum allowable quantity u_i. The planning horizon is n months, each month has a monthly contract quantity allocation b_j ($j=1,...,n$) computed from (2.1). The objective is to determine the minimum amount of fuel to be purchased from contract i for each month j to minimize the expected annual fuel procurement costs while satisfying the contract allocation requirement b_j. Let decision variable x_{ij} be the minimum quantity allocated from contract i to month j. Let the actual quantity of the fuel that we desire to purchase from contact i in month j be defined as:

$$q_{ij} = \frac{x_{ij} \cdot (a_i \cdot l_i + (1 - a_i) \cdot u_i)}{l_i}, \quad a_i \in [0,1] \qquad (2.2)$$

Where a_i is the estimation index. In practice, the estimation index a_i can be justified by the purchasing strategies of the utility. For example, if one supplier is strategically more important than another, the utility may want to purchase considerably more than the minimum quantity from this supplier. On the other hand, index a_i estimates *a priori* the actual contract purchases in anticipation of demand and spot price uncertainty. The contract allocation problem can be stated more formally as follows:

p_{ij} = price of contract i for month j

s_j = per unit spot market price for month j

K_i= maximum number of delivery allowed for contract i

M= a sufficiently large number

$$\textbf{(CAP):} \textit{Minimize } z = \sum_{j=1}^{n} (\sum_{i=1}^{m} p_{ij} \cdot q_{ij} + s_j \cdot (d_j - \sum_{i=1}^{m} q_{ij})) \tag{2.3}$$

$$s.t. \qquad \sum_{i=1}^{m} x_{ij} = b_j, \qquad j = 1, \ldots, n \tag{2.4}$$

$$ {}_{j}^{n} \; x_{ij} \quad l \qquad i \qquad m $$

splitting of contracts over multiple months based on the delivery agreement. Problem (CAP) is similar to a classical transportation problem with the addition of delivery restrictions, a complication that makes the problem much more difficult to solve.

As illustrated in Figure 1, the minimum contract allocation values x_{ij} determined by the above model impose constraints for the monthly procurement decisions described in the following section.

2.2 Phase II: Monthly Procurement Planning Model

Phase II is a rolling horizon, detailed procurement model to be resolved at the beginning of each month. We formulate the base model as a twelve-month horizon linear programme which uses the contract allocation given in Phase I and decisions made in previous months as constraints. This monthly procurement planning (MPP) model is implemented as follows: for any given month j, we divide the twelve month horizon to three basic periods, the current month k, the months before k $(j=1,..,k-1)$, and the future months ($j = k+1,...,n$). As shown in Figure 2, the spot price s_j and demand d_j for each period are set as follows: for the months preceding the current month $(j=1,..,k-1)$ we use actual spot price $\underline{s}_j$ and actual demand $\underline{d}_j$ incurred in these months. For the current month k, we use actual spot price $\underline{s}_k$ and forecast demand d_k. For the future months ($j = k+1,...,n$) we use forecast spot price s_j and demand.

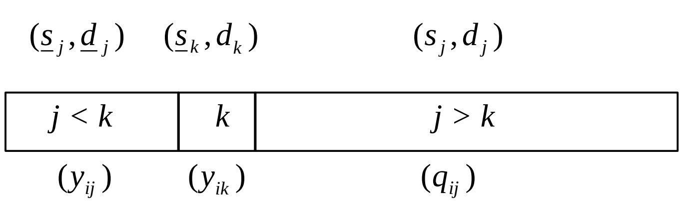

Figure 2. Planning horizon of the monthly procurement model

Given the above setup, up-to-date information concerning demand and spot prices is used for the monthly procurement decision. This model is "rolling horizon" in the sense that when making detailed procurement decision for month *k* we utilize information throughout the twelve-month planning horizon. For any given month *k*, we are given spot prices and demand information, the minimum quantity allocated from contract *i* to *k* (x_{ik} for *i=1,...m),* contract prices, and annual minimum and maximum contract commitments (l_i and u_i respectively) for each contract *i*. Variable y_{ij} specifies the quantity to be purchased from contract *i* during month *j*. As shown in Figure 2, for month *k* we use the actual purchase quantity of earlier months y_{ij} *(j=1,...,k-1)* and the projected purchase quantity for future months q_{ij} *,(j=k+1,...,m)* from (2.2) as inputs. The decision variable is y_{ik} , the quantity to be purchased from contract *i* for current month *k*. The monthly procurement problem is described as follows.

$y_{m+1,j}$ = spot market quantity purchased during month *j, for j£ k*
$q_{m+1,j}$ = estimated spot market quantity purchased for month *j, for j> k*
CC = monthly inventory carrying cost
C_j = quantity carried over from month *j* into month *j+1*

(MPP): The objective of the monthly procurement model is to minimize total fuel procurement cost *c(k)* defined as follows:

(i) total cost of contract purchases

$$c(k) = \sum_{i=1}^{m}\sum_{j=1}^{k-1} p_{ij} . y_{ij} + \sum_{i=1}^{m} p_{ik} . y_{ik} + \sum_{i=1}^{m}\sum_{j=k+1}^{n} p_{ij} . q_{ij} +$$

(ii) total spot market purchases

$$\sum_{j=1}^{k-1} \underline{s}_j . y_{m+1,j} + \underline{s}_k . y_{m+1,k} + \sum_{j=k+1}^{n} s_j . q_{m+1,j} +$$

(iii) total monthly inventory carrying charges for any quantity bought in excess of the demand for the month

$$CC \sum_{j=1}^{n} C_j \qquad (2.9)$$

The constraints used in the model are defined as follows:
(i) the purchase for month *k* is restricted by x_{ik}, minimum quantity allocated for contract *i* in month *k*. If there is nothing allocated from contract *i* for month *k*, set y_{ik} to zero. This constraint enforces the delivery restriction (2.7) specified in Phase I.

$$\begin{aligned} &if\ (x_{ik} > 0)\ then\ (y_{ik} \geq x_{ik}) \quad \forall i \\ &if\ (x_{ik} = 0)\ then\ (y_{ik} = 0) \quad \forall i \end{aligned} \qquad (2.10)$$

(ii) the total contract purchases for each vendor *i* must fall within the range specified by the committed annual maximum. Note that the annual minimum is automatically satisfied by Phase I calculation.

$$\sum_{j=1}^{k} y_{ij} \; + \sum_{j=k+1}^{n} q_{ij} \leq u_i \;\; \forall \;\; i \qquad (2.11)$$

(iii) the sum of all contract purchases and spot market purchases for month *j* and the carryover quantity from the prior month must satisfy the forecast demand of the month

$$\sum_{i=1}^{m+1} y_{ik} + C_{k-1} \;\geq\; d_k \qquad (2.12)$$

(iv) define the carryover quantity for each month as the sum of total contract and spot market purchases for month *j* and the carryover quantity from the prior month, less the demand for *j*.

$$\begin{aligned} C_0 &= 0 \\ C_j &= \sum_{i=1}^{m+1} y_{ij} + C_{j-1} - \underline{d}_j \qquad j = 1,\ldots,k-1 \\ C_j &= \sum_{i=1}^{m+1} y_{ij} + C_{j-1} - d_j \qquad j = k,\ldots,n \end{aligned} \qquad (2.13)$$

(v) non-negativity constraints.

$$y_{ij}, C_j \;\geq\; 0 \qquad (2.14)$$

2.3 A Monte Carlo Testing Environment

In testing and evaluating the two-phase model we setup a Monte Carlo simulation environment for the entire planning period. In the Monte Carlo model, the actual demands and spot prices are generated as a random perturbation from the forecast. The forecasts are generated randomly based on statistical distributions derived from real data. Specifically, the mean and variance for the demand and spot price of each month of the year were estimated from a Normality fit of the historic data. Given the parameters, the demand and spot price forecasts for each month are generated independently, e.g., the January demand and spot price are generated from a Normal distribution derived from the historic January data. In this way, seasonality and other time-related fluctuation over the course of a year is captured.

We first solve the contract allocation problem (CAP) which finds the minimum quantity allocated (x_{ij}) from contract i to month j. This minimum contact allocation becomes input parameters to be used in each monthly procurement problem (MPP) which is resolved at the beginning of each month. This results in a series of twelve linear programs where the output of one month is used as input to all the following months. For instance, the actual purchases y_{i1} ($i=1,\ldots,m+1$) made during January result in either inventory carryover or demand shortfall. In the case of a shortfall, we assume it is automatically filled by the *safety stockpile* (I) (as stated in Section 2) and the usage will be replenished as additional demand requirements for February. In the case of inventory carryover, the additional inventory will be available for future use with a carrying charge. Using the actual spot market price for February, the second linear programming model is adjusted and procurement decisions are generated for February. The results of this model then provide input, as described above, into the model for March. All twelve monthly procurement models are linked in this manner. The actual procurement cost is accumulated and the total cost is calculated at the end of simulation.

3. Solution Methodology

As detailed in Section 2.1 the contract allocation problem (CAP) is formulated as a mixed integer program. For the interest of computational efficiency we developed a local search procedure which utilizes a "pseudo steepest decent" problem space search technique (Storer, Wu and Vaccari, 1993, 1996). A problem space search method requires the use of a problem data vector and a ranking heuristic that generates a solution based on the data vector. A problem space "neighborhood" is generated by perturbing the values of the problem data vector, for each perturbed solution in this neighborhood, a ranking heuristic is used to generate a particular contract allocation solution. The objective value of each is determined using the *original* problem data vector values and the contract allocation solution. A "pseudo steepest descent" problem space search first generates a neighborhood of size *N* from the original problem data, select an incumbent solution from this neighborhood based on the objective, then generate a new size-*N* neighborhood from the incumbent data vector. This process repeats until no improvement is possible, or up to a predetermined number of iterations.

In our implementation of the problem space steepest descent search, we use the spot price vector $(s_1, \ldots, s_n)$ as the problem data vector. The search space is defined by perturbation of the spot price vector. The contract allocation search procedure is described in detail as follows:

(Contract Allocation Heuristic)

Step 0. Initialization. Set incumbent cost $z^* \leftarrow \infty$. Set the incumbent problem data vector as the original spot market price vector, i.e., *set* $\vec{s}$ s s_n

Step 1. Start examining solutions in the *problem space neighborhood* of the incumbent $\vec{s}^{\,*}$. *Initialize* the working problem data vector with the incumbent, *i.e., set* $\vec{s} \leftarrow \vec{s}^{\,*}$.

repeat N times...

begin

Step 2. Initialize the set of unassigned contracts U to all the contracts; set available contract quantity $\tilde{l}$ to its minimum annual quantity, i.e., set $\tilde{l}_i \leftarrow l_i$, *i=1,..,m*..

Step 3. Assign contracts to month. Sort the months *j=1,...,n* in descending order of their spot market prices s_j (as defined by the working problem data vector $\vec{s}$), use [*j*] to index the sorted sequence, i.e., $s_{[1]} \geq s_{[2]} \geq \ldots \geq s_{[n]}$.

for month [j] = 1,..,n do

Sort unassigned contracts in set U in ascending order of their contract prices $p_{i[j]}$, use [*i*] to index the sorted sequence, i.e., $p_{[1][j]} \leq p_{[2][j]} \leq \ldots \leq p_{[|U|][j]}$.

for contract [i]=1,...,|U| do

if $\tilde{l}_{[i]} \leq b_{[j]}$ *then* assign all available quantity of contract [*i*] to month [*j*], i.e., *set* $x_{[i][j]} \leftarrow \tilde{l}_{[i]}, U \leftarrow U / \{i\}$.

Otherwise, assign the available quantity of contract [*i*] to month [*j*] up to the monthly allocation $b_{[j]}$, i.e., *set* $x_{[i][j]} \leftarrow b_{[j]}, \tilde{l}_{[i]} \leftarrow \tilde{l}_{[i]} - b_{[j]}$.

end_do;

end_do;

Step 4. Calculate the current contract allocation cost z (defined by (2.3)) using the <u>original</u> spot price vector $(s_1, s_2, \ldots, s_n)$, and current contract assignment x. Save *z,x* and current problem data vector $\vec{s}$.

Step 5. Perturb each element of the incumbent problem data vector $\vec{s}^{\,*}$ and save it as a working data vector $\vec{s}$ as follows:

$$s_j \leftarrow s_j^* + Uniform\,[-u, u], \quad j=1,...,n$$

(where u is a user defined parameter)

(*go to Step 2)*

end;

Step 6. From the *N* solutions generated in *Steps 2-5*, find *the lowest cost contract allocation*, if its contract allocation cost is less than the current incumbent, then replace the incumbent contract allocation, i.e, if $z < z^*$, *then set* $z^* \leftarrow z, \vec{x} \leftarrow x, \vec{s}^{\,*} \leftarrow \vec{s}$.

Step 7. If there is no improvement in the past two iterations (2N solutions), stop; otherwise, go to *Step 1.*

end;

The steepest decent method generates a neighborhood of size *N*, and examines a maximum of *K* neighborhoods. As shown in *Step 5* we generate alternative neighboring solutions by perturbing spot market prices using a Uniform distribution, i.e.,

$$s_j = s_j + Uniform[-u, u] \qquad j=1,\ldots,n.$$

In each iteration, the search algorithm investigates the neighborhood of the incumbent solution by perturbing the spot market price vector *N* times. The basic strategy of the heuristic is to match "high cost contracts" with months which have "low spot market prices," and vice versa. Each solution *x* is an assignment of the *m* contracts to the *n* months so as to satisfy annual minimum commitment for all the contracts. Each solution is evaluated by the objective *z* as defined in (2.3). Testing of the above heuristic is detailed in Section 4.

4. Computational Experiments

To submit the proposed method for rigorous testing we compare the computational results of the two-phase model with two benchmarks: a multi-stage stochastic programming heuristic developed in (Bonser, Wu and Storer, 1996), and a "perfect information" linear programme (detailed in Section 4.4). We coded the problem space search algorithm for (CAP), the input management for the (MPP) linear programs, and the Monte-Carlo testing environment using FORTRAN 77. The linear programs and the stochastic programme are implemented in FORTRAN with function calls to the LINGO/LINDO. An IBM RS6000 workstation was used for all computational runs. Main purpose of computational experiments is two folds: first, to test the performance of the proposed method by comparing its performance to the two analytic benchmarks, second, to test the robustness of the methods when demand and spot market prices fluctuate. The computational experiments can be summarized as follows:

1. Parameter tuning experiments for the *Contract Allocation Heuristic*

2. Comparing the two-phase method against the rolling horizon stochastic programming heuristic under the following conditions:

2.1 when the actual spot market prices deviate 15%, 30%, 45% and 60% from forecast

2.2 when the actual demand deviates 15%, 30%, 45% and 60% from the forecast

2.3 when the actual demand and spot market prices both deviate (ranging from 15% to 30%) from the forecast

2.4 when a biased forecast (i.e., a strict over- or under-forecast) was made for the spot market prices

2.5 when a seasonal demand variation (peak demands in winter and summer) is imposed

3. Comparing the two-phase method against the "perfect information" linear programming model based on the same conditions specified in (2.1)-(2.5).

In the following sections, we discuss the details of these experiments and their results.

4.1 Experiment 1: Parameter Tuning Experiments for the Contract Allocation Heuristic

Parameter tuning of the *Contract Allocation Heuristic* involves the development and testing of numerous versions of the heuristic and values for the parameters. In this part of the experiment we try to address two particular issues: first, how are the specific design alternatives in the heuristics justified by empirical results, and second, how are specific parameter settings (e.g., the values for parameters N, K and u) of the heuristic tuned according to information available regarding real world data. To demonstrate a broader applicability of these results, the set of instances we use for parameter tuning are different from the instances we use for the remainder of the experiments. Results of the parameter tuning experiments are summarized in Table 1. Details of the parameter tuning experiments can be found in Bonser (1995).

Table 1. Summary of the Parameter Tuning Experiments

Factors	***Levels***
Problem data to be perturbed	*Contract Prices (p_{ij}), Spot Market Prices (s_j)**
Perturbation parameter (r)	*r=.10, and .20**
Neighborhood size (N) and Max. # of iterations (K)	*(N=100, K=100),(N=50,K=100)**
Weighting factor (a)	*.8,.6,.4,.2, and conditional**

** level selected as the result of parameter tuning experiments*

4.2 Experiment 2: Two-Phase Method vs. Rolling Horizon Stochastic Programme

As discussed in Section 2, the multistage stochastic program for procurement planning is not tractable in its original form. Various computational strategies are available which could make the stochastic program more efficient (c.f., Ermoliev and Wets, 1987). In this paper, we use the stochastic programming heuristic (SPH) developed in (Bonser, Wu and Storer, 1996) to establish a benchmark for the proposed two-phase heuristic optimization scheme. This heuristic reduces the size of the scenario space by considering only demand uncertainty and limits the model to solve for three-stages at a time. These three-stage stochastic programs are re-solved monthly and implemented in a rolling-horizon basis for the twelve-month period.

In order to make a fair comparison between the results of the proposed method and SPH, a few modifications had to be made as follows: first, the SPH model assumes a discretized demand distribution, therefore the "actual" demand generated in the Monte-Carlo testing is made consistent to this assumption. Second, the SPH model assumes that the inventory level at the end of the three-month period must be equal to the safety stockpile inventory. Consequently we need to put in an adjustment term when calculating the total procurement cost for the two-phase heuristic. Specifically, if the inventory level at the end of month three was less than the safety stockpile inventory level, additional quantities will be purchased at the spot market price for month three. If excess inventory occurred at the end of month three, then this quantity will be sold at the spot market price for month three. Moreover, a carrying charge is added for the unused portion of the stockpile. Thus, the following term is added to cost of the two-phase model for all comparison with the stochastic program:

$$extra\_cost = s_3 U_3 - s_3 C_3 + CC \cdot I \cdot 3 - CC \cdot \sum_{j=1}^{3} U_j \qquad (4.1)$$

where

remains fairly stable throughout all sub-experiments, we make a general comparison of the CPU requirement for the 10 test instances used in the experiments. The CPU time summarized in Table 2 is reported by running the contract allocation heuristic (Phase I) and the stochastic programme on a IBM RISC/6000 Model 990 machine. As shown in the table, the heuristic generates 12 monthly procurement plans in an average of 2.7 seconds, compared to the average of 370.2 seconds needed for the Stochastic Programming Heuristic. In other words, the contract allocation heuristic takes less than 1% (0.73%) of the time it takes the Stochastic Programming model to reach a solution.

Table 2. Comparison of CPU Requirement on a IBM RS/6000 Model 990

Instances	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*Avg.*
Contract Allocation Heuristic	*2.6*	*2.8*	*2.6*	*2.8*	*2.6*	*2.8*	*2.6*	*2.8*	*2.6*	*2.8*	*2.7 (sec.)*
Stochastic Program	*369*	*366*	*366*	*384*	*381*	*379*	*361*	*362*	*359*	*375*	*370.2 (sec.)*

The time required to run the monthly procurement linear programming model is not included in the table. For the problem tested the LP takes less than 1 CPU second to solve.

Experiment 2.1 - Spot Market Price Fluctuations

In this experiment we consider four different scenarios focusing on the fluctuation of spot market prices from the forecast. The experiments are conducted in the Monte-Carlo testing environment where the actual spot prices ($\underline{s}_j$, $j=1,...,n$) are random variables generated by perturbing the forecast prices (s_j, $j=1,...,n$) as follows:

$$\underline{s}_j = s_j + s_j \cdot pct \cdot Uniform[-1,1] \quad where\ pct = 0.15, 0.30, 0.45, 0.60$$

Table 3 shows the comparison of the two-phase heuristic to the rolling horizon stochastic programming heuristic. Four different scenarios are simulated each corresponding to a different levels of spot price variation (i.e., $pct=0.15,0.30,0.45,0.60$). Each scenario was tested under the five test problems each with two random number seeds (10 replications). The table shows the 12-month simulation results of the two-phase heuristic, and the simulation results of implementing the stochastic programming model in a rolling horizon. The 95% confidence intervals of the mean, and the minimum, average and maximum percentage differences of the two methods are computed from 10 replications.

As shown in the table the two-phase heuristic produces comparable results as those produced by the SPH model. When the level of spot price perturbation (*pct)* reaches a higher level, the heuristic appears to behave in a more robust fashion when compared to the stochastic program. Not only does the average percentage difference favor the heuristic (-2.959% and -1.206%), the means are lower and the confidence intervals are narrower. Note that both the heuristic and the stochastic program uses forecast spot prices for future months while using actual spot prices for the current and past months.

Table 3. Two-Phase Heuristic vs. Rolling Horizon SPH Under Spot Price Variations

	Two-Phase Heuristic		*Stochastic Programming*		*Percentage Difference**		
Spot Price Variations (pct)	*mean*	*95% confidence level***	*mean*	*95% confidence level*	*min*	*avg.*	*max*
0.15	*276232.0*	*13986.22*	*276156.6*	*14307.22*	*-2.1*	*0.047*	*1.45*
0.30	*276539.8*	*15245.55*	*276194.4*	*14755.12*	*-3.73*	*0.1339*	*3.98*
0.45	*264399.0*	*10563.74*	*273402.8*	*16705.75*	*-9.15*	*-2.959*	*3.45*
0.60	*260812.7*	*10363.29*	*264268.7*	*12224.15*	*-6.7*	*-1.206*	*3.62*

**Percentage Difference of the two methods; calculated as (v(Heuristic)-v(SPH))/v(SPH)) in %*
***95% confidence level of mean; calculated from 10 replications*

Experiment 2.2 - Demand Level Variations

This experiment is similar to that of 2.1 except that we consider demand level variations from the forecast. The experiments are conducted in the Monte-Carlo testing environment where the actual demand levels ($\underline{d}_j$, $j=1,...,n$) are random variables generated by perturbing the forecast demands (d_j, $j=1,...,n$) as follows:

$$\underline{d}_{\mathrm{j}} = d_j + d_j \cdot pct \cdot Uniform[-1,1] \quad where\ pct = 0.15, 0.30, 0.45, 0.60$$

parameter fluctuates in an erratic fashion (as in Experiments 2.1 and 2.2). Both methods appear to be quite robust under either condition.

Table 5. Two-Phase Method vs. Rolling Horizon SP when Spot Prices and Demand Both Vary

	Two-Phase Heuristic		*Stochastic Programming*		*Percentage Difference*		
Scenarios (demand,spot)	*mean*	*95% Confidence Level*	*mean*	*95% Confidence Level*	*min*	*avg.*	*max*
(0.15,0.15)	*274050.1*	*10441.09*	*272794.6*	*9806.38*	*-0.98*	*0.446*	*1.45*
(0.15,0.30)	*274223.6*	*11037.80*	*272467.5*	*10865.45*	*-2.06*	*0.660*	*4.24*
(0.30,0.15)	*284215.4*	*15752.45*	*285571.2*	*13111.08*	*-4.56*	*-0.562*	*1.96*
(0.30,0.30)	*288701.0*	*19150.43*	*288056.7*	*14364.36*	*-4.91*	*0.079*	*5.23*

Experiment 2.4 - Forecast Bias On Spot Market Prices

In the previous experiments the demand and/or spot price fluctuations are centered at the original forecast. Despite of the level of fluctuation the forecast still represents an accurate estimation of the population mean. In this experiment we test the performance of the two methods when the forecast does not estimate the population mean correctly. Table 6 summarizes the simulation results where the forecast spot market prices underestimate the actual by up to 30% (i.e., the actual prices are randomly generated from the forecast prices anywhere from 0 to 30% higher), or overestimate the actual by up to 30%. The two scenarios are marked *30%-under* and *30%-over*, respectively. As shown in the table, the heuristic and the stochastic program again demonstrate comparable results. In the case where the forecast over-estimate the actual spot prices, the heuristic appear to better take advantage of the situation, showing a lower mean and narrower confidence interval.

Experiment 2.5 - Seasonal Demand Variations

In the previous experiments the demand variation are applied uniformly to all the months of the year. But in reality, the level of demand variation often reflects a seasonal trend. For example, the demand is likely to fluctuate more in the summer and winter months when a particularly hot or cold weather pattern could change the short-term demand drastically. In Spring and Fall months drastic changes are less likely. To test the robustness of the two methods under these conditions we tested two particular scenarios where the actual demand varies from the forecast by up to 30% (in scenario 1), and 45% (in scenario 2) for the winter and summer peaking months of December, January, February, June, July, and August. The remaining months have demand variation up to 15% (i.e., *pct* = 0.15). In this set of experiments we examine 15 replications for each method since a higher level of variation is expected. The results are summarized in Table 6. As shown in the table, in both seasonal demand fluctuation cases, the stochastic program appear to be more robust. Showing both a lower mean and narrower confidence interval. However the average difference of the two methods is only 2.082%.

Table 6. Comparison under Biased Forecast and under Seasonal Effects

	Two-Phase Heuristic		*Stochastic Programming*		*Percentage Difference*		
Scenarios	*mean*	*95% Confidence Level*	*mean*	*95% Confidence Level*	*min*	*avg.*	*max*
30% under	*293040.0*	*17301.36*	*291632.5*	*18493.02*	*-1.60*	*0.549*	*2.28*
30% over	*271799.6*	*12665.97*	*273400.5*	*15458.76*	*-3.86*	*-0.449*	*2.78*
Seasonal-30%	*295918.2*	*9859.309*	*289887.3*	*9075.47*	*0.46*	*2.082*	*5.35*

4.3 Experiment 3: Two-Phase Heuristic vs. The Perfect Information Benchmark

To establish an additional set of results for comparison in a 12-month planning horizon, we construct a "perfect information" benchmark as follows: first use the Monte Carlo testing environment (Section 2.3) for the testing of the two-phase search heuristic. During the Monte Carlo experiments we record the "actual" demand ($\underline{d}_j$) and spot prices ($\underline{s}_j$) generated by simulation. Using this "hindsight" perfect information (i.e., setting $d_j \leftarrow \underline{d}_j, s_j \leftarrow \underline{s}_j, \forall j$), we solve the (*MPP)* linear programme described by (2.9)-(2.14) in Sections 2.2. The solution of the linear programme is optimal if the decision-maker had access to perfect future information concerning demand and spot market prices. Obviously, this optimum model does not exist in reality, however it establishes a theoretical optimal given a specific demand and spot market price scenario. Input to the perfect information model includes actual contract costs, quantity commitments, actual monthly demand quantities, and actual monthly spot market prices. Inventory carrying charges for the safety stockpile are also included as a monthly cost.

The same five sets of experiments (2.1-2.5) described in previous section were repeated for the comparison between the two-phase optimization heuristic and the perfect information linear programming model (experiments 3.1-3.5). The objective function used in this experiment is slightly different from the one used in Experiments 2 in that the extra cost term (4.1) can be dropped since we are not comparing to the stochastic program. We instead use the objective function defined by (2.9). The results for experiments 3 are summarized in Tables 7-10. As shown in Table 7, the average percentage from optimum increases as the level of spot price variation increases (from 2.587% to 10.078%). This result is to be expected in that the heuristic uses forecast spot price for the contract allocation. The heuristic solutions appear to be quite robust even under a 60% price perturbation.

Table 7. Two-Phase Heuristic vs. Perfect Information Optimum Under Spot Price Variations

	Two-Phase Heuristic		*Perfect Information Optimum*		
Spot Price Variations (pct)	*mean*	*95% Confidence Level*	*mean*	*95% Confidence Level*	*Avg. Percentage From Optimum*
0.15	*278177.2*	*15024.60*	*271199.9*	*14815.04*	*2.587*
0.30	*277618.3*	*15902.74*	*265709.9*	*14733.83*	*4.463*
0.45	*266077.6*	*11263.91*	*249818.4*	*11500.57*	*6.576*
0.60	*263162.4*	*11144.98*	*239244.2*	*11540.48*	*10.078*

Table 8 shows a similar effect of the demand perturbation where the percentage from optimum increases as the level of perturbation increases. Under a 60% perturbation in demand the heuristic only shows an average of 4.099% deviation from the perfect information optimum.

Table 8. Two-Phase Heuristic vs. Perfect Information Optimum Under Demand Variations

	Two-Phase Heuristic		Perfect Information Optimum		
Demand Level Variations (pct)	mean	95% Confidence Level	mean	95% Confidence Level	Percentage from Optimum
0.15	279778.4	11282.21	276211.2	10852.17	1.283
0.30	295899.7	17256.75	289615.6	17775.49	2.222
0.45	277248.3	14133.51	268855.0	16054.49	3.264
0.60	287026.0	12934.23	275853.2	12929.23	4.099

Table 9 shows the test cases where both spot prices and demands are perturbed. Consistent with our findings in Tables 8-9, the spot price variation appears to have a somewhat bigger impact to the robustness of the heuristic (i.e., the percentage from optimum is 4.294% for the (0.15,0.30) combination and 3.078% for the (0.30,0.15) combination).

Table 9. Comparison under Varying Spot Prices and Demand Levels

	Two-Phase Heuristic		*Perfect Information Optimum*		
Scenarios (demand, spot)	*mean*	*95% Confidence Level*	*mean*	*95% Confidence Level*	*Percentage from Optimum*
(0.15,0.15)	*275425.9*	*10484.13*	*269595.0*	*10331.49*	*2.165*
(0.15,0.30)	*274873.1*	*11079.36*	*263471.0*	*9541.60*	*4.294*
(0.30,0.15)	*290095.4*	*16517.60*	*281509.3*	*16443.60*	*3.078*
(0.30,0.30)	*293153.7*	*19496.45*	*279833.9*	*20099.49*	*4.873*

As shown in Table 10, when tested under the cases of forecast bias, the heuristic appears to be more sensitive to the cases where the actual spot prices is up to 30% lower than forecast. This result represents the case when the heuristic is misled by the forecast information and over-commits to contract purchases. As a result, it is unable to take full advantage of the lower spot prices. On the other hand, when the actual spot price is higher then forecast, the heuristic is able to allocate more contract-purchases for an overall lower cost. The seasonal demand variation does not seem to affect the heuristic robustness.

Table 10. Comparison Under Biased Forecast and Seasonal Demand Variation

	Two-Phase Heuristic		*Perfect Information Optimum*		
Scenarios	*mean*	*95% Confidence Level*	*mean*	*95% Confidence Level*	*Avg. Percentage from Optimum*
30% Over	*294710.9*	*18388.05*	*287200.1*	*17403.32*	*2.598*
30%Under	*273246.8*	*13525.93*	*257328.2*	*12645.77*	*6.196*
Seasonal-30%	*297960.7*	*12404.54*	*296904.3*	*12206.89*	*0.353*
Seasonal-45%	*272202.4*	*10594.87*	*265533.5*	*10120.66*	*2.510*

5. Conclusions

We developed a two-phase optimization model for the fuel procurement problem. The optimization heuristic first allocates contract purchases over the course of a year, balancing contract commitment and expected spot market purchases, then solve in a rolling horizon fashion the computer time. We further demonstrate the robustness of the heuristic scheme by comparing its performance to a perfect information benchmark.

In the following, we outline some general insights provided in the study, which may be of broader managerial interests.

1. The model tends to assign low-priced contracts to month with high forecasted spot market prices, and vice versa. This is because the *Contract Allocation Heuristic* uses this as a basic strategy then perturbs the spot market prices randomly to generate the search neighborhood. Several other strategies have also been tested, for instance, assigning the low-priced contracts to earlier months regardless of the spot price forecast. Or, perturbing the contract prices to generate alternative solutions. These strategies are screened out during the tuning experiments.
2. Most contract allocations do not split the contracts over more than two or three months since most contracts limit the number of deliveries per year (typically K#3). Most of the splitting can be attributed to the level of minimum annual contract commitment and projected monthly demand. Obviously when an annual contract commitment is much larger than any monthly demand, splitting would be necessary.
3. When compared to the perfect information results, the most significant performance deviation occurs when the spot prices are consistently under-estimated (by 30%), and when the spot price fluctuates more than 45% from the forecast. Both of these cases make intuitive sense since *a priori* planning are indeed sensitive to the quality of *a priori* information available. Unfortunately, in practice spot prices are driven by complex economic indexes and are very difficult to forecast. The stochastic programming approach runs into the same difficulty since

incorporating spot price scenarios would require *a priori* statistical information about the prices.

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Table 2. Results Summary: Two-Phase Method vs. Stochastic Programming Optimum

	Stochastic Programming optimum					Two-Phase Optimization Heuristic			
	E(z)	*95% Confidence*[*]		*99% Confidence*[*]		*z value*	% from best[**]		
Test Sets		lower	upper	lower	upper	(avg.)	min.	avg.	max.
1	76,910	72,688	79,933	71,107	81,514	76,310	-12.57	-0.78	11.88
2	59,350	56,173	64,862	54,276	66,759	60,517	-12.12	1.97	17.60
3	70,010	65,228	72,232	63,699	73,760	68,729	-11.32	-1.83	10.44

** 95% (or 99%)confidence interval calculated for each test set; lower and upper represent the lower and upper limits of the confidence interval*

** % from best is calculated as (*v(Heuristic)-v(SP optimal))/v(heuristic)) where v(x) represent value of x*