A decision support system for forecasting and optimal procurement

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ABSTRACT

Optimal procurement in most industries involve forecasting of two quantities: prices of raw materials and customer's demand. The aim of this work is to integrate forecasts into production planning models, with the aim of minimizing overall procurement, holding and production costs under demand satisfaction constraints. The decision support system should allow the decision maker to integrate qualitative, unstructured information through a simple interface, for scenario selection and solution refinement

PROBLEM DEFINITION

1.1 INTRODUCTION

This problem is variation of lot sizing problem in stochastic setting. Variation is as follows. We have stochastic prediction for raw material supply cost \mathbf{s} at future time moment t. The *factory* converts all bought raw materials at time t and stores them into a warehouse. Number of discrete time moments is denoted by n.

One time moment storage costs fixed amount h, that is the holding cost.

Likewise demand for the product is equally stochastic, denoted as \mathbf{d} . In case there's no products in storage to satisfy demand we pay backlogging cost denoted as b.

Our aim is to optimize our procurement policy by variating \mathbf{x} , that is product amount we buy at time moment t. However we are constrained by the maximum raw materials we can buy each day by \mathbf{x}_{max} .

1.2 FORMAL PROBLEM DEFINITION

1.2.1 Definitions

Every input value is known beforehand, and it's assumed for random variables their distributions are known. Following is deterministic problem variant, and in subsequent chapters randomness and uncertainty is embedded into problem. Font convention:

x, y, z	variables and constants
x, y, z	vector variables and constants
X, Y, Z	random variables
X, Y, Z	random vectors
$\mathcal{X}, \mathcal{Y}, \mathcal{Z}$	probability distributions
A, B, C	matrices, by context differentiated from random vectors

Now following is formal problem description for deterministic variant:

$$\mathbf{s} = [s_1, s_2, \dots, s_n]^\mathsf{T}$$
 Supply cost vector $\mathbf{x} = [x_1, x_2, \dots, x_n]^\mathsf{T}$ Procurement quantity vector \mathbf{x}_{\max} Procurement quantity limits vector $\mathbf{d} = [d_1, d_2, \dots, d_n]^\mathsf{T}$ Demand random vector, Y_t is a random variable backlogging cost holding cost

1.2.2 Variables

x is our decision variable, as described previously.

1.2.3 Constraints

$$\mathbf{x} \in \mathbb{N}_0^n$$
$$\mathbf{x} \le \mathbf{x}_{\text{max}}$$
$$\sum x = \sum d$$

1.3 OBJECTIVE FUNCTION

First let's define auxiliary matrix:

Definition 1.3.1. C matrix defines cost for satisfying demand with specific raw supply material purchase date. It's element c_{ij} equals:

$$c_{ij} = \begin{cases} b(i-j) + s_i & j < i \\ h(j-i) + s_i & j \ge i \end{cases}$$

That is using purchaces raw materials at i to satisfy demand at time moment j incurs cost c_{ij} .

Definition 1.3.2. c(t) defines total speeding we pay at time t.

$$c(t) = \sum_{i} x_i c_{it} \tag{1}$$

Definition 1.3.3. $f(\mathbf{x})$ is objective function for this problem. Our aim is to minimize it.

$$f(\mathbf{x}) = \sum_{t} c(t) \tag{2}$$

DETERMINISTIC APPROACH

2.1 SOLUTION

Problem as defined in 1 can be reduced to transportation problem¹ since we have cost matrix **C** defining "transportation" costs associated with each possible assignment option. For successful reduction we only need adding dummy source or destination as described in²

2.2 VARIANTS

Problem as defined previously could seem rather simplistic and not allowing useful extensions users might want, such as current storage amount and similar. In following few subsections most useful extensions are described.

Starting storage capacity

in case we have already certain number of product in stock we can easily embed that knowledge into model by adding new supplier/node as new decision variable x_0 . It's maximum, $x_{\max 0}$ is equal to starting storage capacity, and $c_{0j} = (j-1)h$

Ending storage requirement

For example we'd like to have some extra product in stock by the end of analysis, and it's quite easy to accommodate such requirement. Simple add to d_n ending storage requirement, thus obtaining new d_n .

¹ Frederick S Hillier. Introduction to Operations Research. McGraw-Hill, 2014. ISBN: 0073523453.

² Ibid.

Allowing future backlogging

In model as described, time stops at time moment n, however, in realistic scenario we're looking at only short time snapshot of ongoing process. To allow such future purchases to backlog at previous times, we can extend the model with m future moments:

 $d_{n+i} = 0$ $x_{\max n+i} = y_i$ allowable backlogging from future supply purchases \mathbf{C} as previously defined, simply extended \mathbf{s} extended with future costs

for i in 1, 2, . . . , m:

DEEPER ANALYSIS

First we are going to analise problem deeply without presuming any independence or probability distribution on random variables. Later in subsequent chapters we are going to focus more on where demand at time *t* has independent Gaussian distribution and mean.

3.1 COST FUNCTION

The minimizing function is:

$$E\left[\mathbf{s}^{\mathsf{T}}\mathbf{x} + \sum c(t)\right]$$

Due to linerality of expectation and *x* being variable it's equal to:

$$\mathbf{x} \operatorname{E} \left[\mathbf{s}^{\intercal} \right] + \operatorname{E} \left[\sum c(t) \right]$$

Therefore only needed modeling information for supply cost is its expectation $E[\mathbf{s}]$. The other part is more trickier since D_i and D_j aren't usually independent.

3.2 HANDLING DEMAND COST NON-LINEARITY

As we can see in equation 1 we have non-linearity depending whether we're satisfying all demand or are we backlogging demand at time t. Therefore here are two possible solutions for minimizing objective function 2.

Simulation

We generate multiple scenarios for demand vector, d according to probability distribution. For small n and relatively small number of outcomes in each ran-

dom variable we can exhaustedly model each scenario, scale it appropriately and feed to MIP solver¹

Safety net approach

Alternatively, we can artificially add new constraints and avoiding backlogging with arbitrary probably. This model assumes backlogging cost are significantly greater than storage cost, that is backlogging penalty is severe.

Thus we chose values arbitrary realizations of random variables D_t and add additional constraints of the form:

$$X_t \ge D_i \ \forall t$$
 (3)

which reduces cost function 1 to:

$$c(t) = h(X_i - D_i) X_i \ge D_i$$

and enables are faster solving approaches. Given parameters D_i chosen and their underlying distribution we derive non-increasing function p(t) which represent probability of not breaking newly introduced constraints 3

Min-cost max flow with uncertaintiy

Since deterministic case can be modeled with min-cost max flow, we can investigate further in this directi

Stochastic Dynamic Programmnig

TODO.. maybe, I've got recommendation by a friend, need to read some papers.

¹ There's a trick on using binary variable for discontinuity in cost function 1

BIBLIOGRAPHY

Hillier, Frederick S. *Introduction to Operations Research*. McGraw-Hill, 2014. ISBN: 0073523453.