INSIM: AN INTERACTIVE INVENTORY SIMULATION

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Inventory systems exhibit behavior important in systems analysis. They lend themselves to “solution” both via simulation and formal analysis, and provide a basis for demonstrating varying levels of system sophistication. [7] Under conditions of certainty, inventory control is simple. With demand and lead time know-n, a new order would be placed when the number of items on hand plus the number of units on order will exactly satisfy demand over the time period required for the new order. The inventory level will fall to zero each day an order is received and demand can never exceed the inventory level. [3] Management under certainty is, of course, not realistic and the volatility of demand and the unreliability of lead time combined to exacerbate the inventory control problem.

The cost of ignoring variable lead time [9] coupled with probabilistic and deterministic demand [4] invalidates most simplistic models. In fact the cost component it self can be rather complex. With lost demand resulting in lost revenues and potentially impacting the demand function for the firm measuring lost profits can become quite complex. In an effort to better model variable lead time and demand a variety of techniques have been employed. Several studies have investigated known distributions in an effort to describe these stochastic processes. [2] While in a few cases known distributions are representative of the actual distribution found in the real world environment, for the most part they are not good proxies of the actual process. Others have evaluated aggregate techniques versus single item models [8] in an effort to achieve better prediction at a more macro level. Though success in this area has often been good, the requirement for detailed inventory control is still present. This paper demonstrates a simulation approach to evaluating the cost of inventory control and suggests methods for seeking “optimum” solutions to the inventory cost function. The model breaks no new ground in the field of inventory control, but in conjunction with the simulation allows students to manipulate the determinants of the inventory cost function and develop an appreciation for the sensitivity and impact of each on total cost. The program is written in ANS FORTRAN and is available from the author.

The Model

The simulation model assumes that:

1. Unfilled demand can be backlogged and satisfied when items become available. An alternative assumption which can be readily implemented would have all or a portion of unfilled demand as lost demand.

2. Unfilled demand does not impact the demand function. Thus, backlogged orders do not discourage customers. This assumption is not realistic with respect to real world behavior. The model can be readily adapted to accommodate a decay function with demand decreasing with increased backlog.

3. The cost of a stockout is fixed and does not exhibit any compounding effect; it is additive and linear. Again this is not a realistic assumption. A more accurate model would incorporate a geometric increase in stockout cost as increased backlogs occur. This adaptation can be readily implemented given a user defined cost function.

4. The cost of an inventory item is constant during the entire simulation. During periods of high inflation this could be a costly assumption. An inflationary factor can be added to increase the cost of an inventory item by a prescribed amount from period to period to reflect inflationary impact.

5. The annual interest rate used in the holding cost function is constant during the entire simulation. Though a tenuous assumption the annual interest rate is not an easy component to forecast. As such an assumption of stability is probably no less valid than rather uncertain estimates of changing annual interest rates.

6. There are no constraints on crossing orders. Thus goods ordered in period two could in fact arrive later than goods ordered in period three.

7. The user provides lead time and demand information in the form of decrete probability distributions. Alternative approaches include built in distributions from which the user might select.

This feature has not been implemented and thus the model always requires historical data.

8. The model reflects a single channel dealing only with one item and one source of supply.

The model is composed of user defined constants (see the appendix for user documentation), random (probabilistic) variables, and deterministic variables. They are constants:

RC Receiving cost
OC Ordering cost
SOC Stockout cost
VII Value of an inventory item
AIR Annual interest rate
RP Reorderpoint
RQ Reorder quantity

deterministic variables:

BBL_i Beginning backlog in period i

BL_i. Backlog in period i

BI_i Beginning inventory in period i

EI_i Ending inventory in period i

UOO_i Units on order in period I

O_i Units to be received in period I

NO_i Number of orders to be received in period I

OCC_i Ordering cost in period i

and the probabilistic variables:

ID_i Demand in period I
LT_i Lead time for order placed in period i

The total cost (TC) function can be written as

$$TC = \Sigma NO_i RC + \Sigma OCC_i + \Sigma BL_i SOC + \Sigma(((BI_i + EI_i)/2.0)VII.AIR)/52$$

where $EI_i \geq 0$

In each period i of the simulation (a week in this model)

ID_i is a random variable

LT_i is a random variable

and we compute

$BBL_i = BL_{i-1}$

$BI_i = EI_{i-1} + O_i$

$UOO_i = UOO_{i-1} - O_i$

where an order is placed if

$BI_i + UOO_i - BBL_i - RP \leq 0$

$NO_{i+LT_i} = NO_{i+LT_i} + 1$

$OCC_i = OC$

else

No orders are placed

and

$OCC_i = 0$

Then we compute

$EI_i = BI_i - ID_i + BBL_i$

should

$EI_i < 0$

a backlog occurs and

$BL_i = ABS(EI_i)$

$EI_i = 0.$

The random variables demand and lead time are input as discrete probability distributions and are assumed to represent historical experience.

Future extensions to the program could include forecasting demand using various types of naive or more complex multiple regression models, The user defined constants reflect the item and environment being modeled. The reorder point, RP, and reorder quantity, RQ are set by the user who can then in subsequent runs manipulate these variables and observe their impact on the total cost function. While Earl and Chapman [3] used a gradient search technique to try to optimize RP and RQ, INSIM does not seek an optimum. The student is normally provided with several search strategies and both the batch and interactive versions of INSIM allow for easy experimentation with RP and RQ; in fact, all user defined variables can be easily altered and the simulation repeated.

The assumptions implemented in the current version of INSIM are not necessarily the most appropriate in each instance but in total are intended to provide a “reasonably” realistic simulation. It is the author’s intent to let INSIM serve as a “breadboard” and thus provide a starting point for other enhancements or alternative assumptions. Given the modular design of INSIM other considerations could be implemented as options or different versions of the model. Future extensions will evaluate these alternative formulations as well as the following optimization routines.

Future Development

Given that the demand and lead time probability density functions are seldom known (though often assumed to approximate known distributions [2]), an analytical solution is not realistically attainable. Therefore, a highly reliable nonderivative search method is probably the best available alternative for identifying “optimum” values for inventory control. This, coupled with accurate demand and lead time estimates could produce a very realistic model for teaching and setting inventory policy.

As indicated Earl and Chapman used a gradient search technique to locate the optimum values for RP and RQ. They point out however, that their gradient method algorithm will sometimes yield values of RP and RQ that are <u>not</u> near optimal. Himmelblau [5] references a generalized gradient search program developed by K. E. Cross and W. L. Kephart of Union Carbide Corporation, Oakridge, Tennessee. Their algorithm can accommodate both linear and nonlinear equality and inequality constraints and is available as share release SDA3541. The program incorporates several special strategies to handle such problems as ridges and trivial constraints as well as the ability to accelerate the optimization. A projection technique is also incorporated to reach a feasible point from a nonfeasible starting point.

Using INSIM, this author has investigated several search techniques in addition to the generalized gradient search. Though no definitive results are yet available, several methods look good. Among those showing early promise are the flexible polyhedron search, Powell's method, and Hooke-Jeeves. For a detailed explanation of these and other derivative and nonderivative methods the reader is referred to <u>Applied Nonlinear Programming</u>.

Because of the major impact of inventory policy on the firms total cost function, realistic models and optimization methods can be of great value to the decision maker. However, the author would urge caution at this point in the modeling of the firms inventory system. Often in an attempt to rigorously quantify inventory activity many other interrelated variables are totally disregarded; for example transportation and other channel costs. It is essential that the model builder be acutely aware of the inherent limitation of the model formulation in order to not generalize beyond these built in limitations. It is the author's hope that with the work of Earl and Chapman, the other authors cited, and all those interested in realistic real-world approximations, meaningful decision models will be developed for use by educators and practitioners.

REFERENCES

1. Agin, Norman, “A Mm-Max Inventory Model,” Management Science, Vol. 12, No. 7, March 1966, pp. 517-529.

2. Burgin, T. A., “The Gamma Distribution and Inventory Control,” Operations Research Quarterly, Vol. 26, No. 3i, pp. 507-525.

3. Earl, Thomas E. and Chapman, Randall G., “Inventory Control Simulation,” Fortran Applications in Business Administration, Vol. II, Thomas J. Schriber and Laurence A. Madeo, eds., The University of Michigan, 1970.

4. Hausman, Warren and Thomas, L. Joseph, “Inventory Control with Probabilistic Demand and Periodic Withdrawals,” Management Science, Vol. 18, No. 5, January 1972, pp. 265-275.

5. Himmelblau, David M., Applied Nonlinear Programming, New York: McGraw-Hill, 1972.

6. Kochenberger, Gary A., “Inventory Models: Optimization by Geometric Programming,” Decision Science, Vol. 2, No. 2, April 1971, pp. 193-205.

7. McMillan, Claude and Gonzalez, Richard F., Systems Analysis A Computer Approach to Decision Models, Illinois: Richard D. Irwin, 1973.

8. Thomas, H. E., “Quadratic Inventory Cost Approximation and the Aggregation of Industrial Products,” Management Science, Vol. 19, No. 11, July 1973.

9. Vinson, Charles, “The Cost of Ignoring Lead Time Unreliability in Inventory Theory,” Decision Sciences, Vol. 3, No. 2, April 1972, pp. 87-105.

APPENDIX

INSIM is available in both the batch and interactive environment. The following outlines the setup and execution procedure for running INSIM interactively.

INSIM will ask the user for starting values. The variables and their abbreviations are listed below.

Description	Abbreviation
The number of periods to be simulated	NP
Value of an inventory item	VI
Beginning inventory level	BI
Reorder point	RP
Reorder quantity	RQ
Order cost	OC
Receiving cost	RC
Stock out cost	SO
Annual interest rate	IR
Number of lead times	LT
Number of demand quantities	DQ

Given the following demand and lead time distributions:

Weekly Demand (units)	Frequency	Lead time Length (weeks)	Frequency
121	40	1	7
131	62	2	10
141	70	3	30
151	60		47
161	28		
	260		

compute the cumulative probability for each occurrence in each distribution.

Demand	
121	.15
131	.39
141	.66
151	.89
161	1.00

Lead Time	
1	.15
2	.36
3	1.00

INSIM will now ask for LT lead times, and then LT lead time cumulative probabilities. INSIM will then ask for DQ demand quantities and then DQ demand quantity cumulative probabilities. Once this information has been entered, INSIM will perform the simulation and display the simulation results.

After displaying the results, INSIM will ask if the simulation is to be run again. A YES response causes INSIM to ask if the value of any of the simulation control variables are to be changed. Using the abbreviation form the user can selectively change the values and then by saying RUN execute the simulation again. Future enhancements call for printing comparative statistics, plotting total cost against selected variables, and implementation of an optimization routine to locate optimum values for RP and RQ.