

Supply chains involve many risks, as we have seen. Modeling that risk focuses on probability, a well-developed analytic technique. This chapter addresses basic simulation models involving supply chains, to include inventory modeling (often accomplished through system dynamics) and Monte Carlo simulation of vendor outsourcing decisions.

Inventory Systems

Inventory is any resource that is set aside for future use. Inventory is necessary because the demand and supply of goods usually are not perfectly matched at any given time or place. Many different types of inventories exist. Examples include raw materials (such as coal, crude oil, cotton), semi-finished products (aluminum ingots, plastic sheets, lumber), and finished products (cans of food, computer terminals, shirts). Inventories can also be human resources (standby crews and trainees), financial resources (cash on hand, accounts receivable), and other resources such as airplanes seats.

The basic risks associated with inventories are the risks of stocking out (and thus losing sales), and the counter risk of going broke because excessive cash flow is tied up in inventory. The problem is made interesting because demand is almost always uncertain, driven by the behavior of the market, usually many people making spontaneous purchasing decisions.

Inventories represent a considerable investment for many organizations; thus, it is important that they be managed well. Although many analytic models for managing inventories exist, the complexity of many practical situations often requires simulation.

The two basic inventory decisions that managers face are *how much* to order or produce additional inventory, and *when* to order or produce it. Although it is possible to consider these two decisions separately, they are so closely related

that a simultaneous solution is usually necessary. Typically, the objective is to minimize total inventory costs.

Total inventory cost can include four components: holding costs, ordering costs, shortage costs, and purchasing costs. **Holding costs**, or *carrying costs*, represent costs associated with maintaining inventory. These costs include interest incurred or the opportunity cost of having capital tied up in inventories; storage costs such as insurance, taxes, rental fees, utilities, and other maintenance costs of storage space; warehousing or storage operation costs, including handling, record keeping, information processing, and actual physical inventory expenses; and costs associated with deterioration, shrinkage, obsolescence, and damage. Total holding costs are dependent on how many items are stored and for how long they are stored. Therefore, holding costs are expressed in terms of *dollars associated with carrying one unit of inventory for unit of time*

Ordering costs represent costs associated with replenishing inventories. These costs are not dependent on how many items are ordered at a time, but on the number of orders that are prepared. Ordering costs include overhead, clerical work, data processing, and other expenses that are incurred in searching for supply sources, as well as costs associated with purchasing, expediting, transporting, receiving, and inspecting. In manufacturing operations, **setup cost** is the equivalent to ordering cost. Set-up costs are incurred when a factory production line has to be shut down in order to reorganize machinery and tools for a new production run. Set-up costs include the cost of labor and other time-related costs required to prepare for the new product run. We usually assume that the ordering or setup cost is constant and is expressed in terms of *dollars per order*.

Shortage costs, or *stock-out costs*, are those costs that occur when demand exceeds available inventory in stock. A shortage may be handled as a *backorder*, in which a customer waits until the item is available, or as a *lost sale*. In either case, a shortage represents lost profit and possible loss of future sales. Shortage costs depend on how much shortage has occurred and sometimes for how long. Shortage costs are expressed in terms of *dollar cost per unit of short item*.

Purchasing costs are what firms pay for the material or goods. In most inventory models, the price of materials is the same regardless of the quantity purchased; in this case, purchasing costs can be ignored. However, when price varies by quantity purchased, called the *quantity discount* case, inventory analysis must be adjusted to account for this difference.

Basic Inventory Simulation Model

Many models contain variables that change continuously over time. One example would be a model of a retail store's inventory. The number of items change gradually (though discretely) over an extended time period; however, for all intents and purposes, they may be treated as continuous. As customer demand is fulfilled, inventory is depleted, leading to factory orders to replenish the stock. As orders are received from suppliers, the inventory increases. Over time, particularly if orders

are relatively small and frequent as we see in just-in-time environments, the inventory level can be represented by a smooth, continuous, function.

We can build a simple inventory simulation model beginning with a spreadsheet model as shown in Table 5.1. Model parameters include a holding rate of 0.8 per item per day, an order rate of 300 for each order placed, a purchase price of 90, and a sales price of 130. The decision variables are when to order (when the end of day quantity drops below the reorder point (ROP), and the quantity ordered (Q). The model itself has a row for each day (here 30 days are modeled). Each day has a starting inventory (column B) and a probabilistic demand (column C) generated from a normal distribution with a mean of 100 and a standard deviation of 10. Demand is made integer. Sales (column D) are equal to the minimum of the starting quantity and demand. End of day inventory (column E) is the maximum of 0 or starting inventory minus demand. The quantity ordered at the end of each day in column F (here assumed to be on hand at the beginning of the next day) is 0 if ending inventory exceeds ROP, or Q if ending inventory drops at or below ROP.

Profit and shortage are calculated to the right of the basic inventory model. Column G calculates holding cost by multiplying the parameter in cell B2 times the ending inventory quantity for each day, and summing over the 30 days in cell G5. Order costs are calculated by day as \$300 if an order is placed that day, and 0 otherwise, with the monthly total ordering cost accumulated in cell H5. Cell I5 calculates total purchasing cost, cell J5 total revenue, and cell H3 calculates net profit considering the value of starting inventory and ending inventory. Column K identifies sales lost (SHORT), with cell K5 accumulating these for the month.

Crystal Ball simulation software allows introduction of three types of special variables. Probabilistic variables (assumption cells in Crystal Ball terminology) are modeled in column C using a normal distribution (CB.Normal (mean, std)). Decision variables are modeled for ROP (cell E1) and Q (cell E2). Crystal Ball allows setting minimum and maximum levels for decision variables, as well as step size. Here we used ROP values of 80, 100, 120, and 140, and Q values of 100, 110, 120, 130 and 140. The third type of variable is a forecast cell. We have forecast cells for net profit (H3) and for sales lost (cell K3).

The Crystal Ball simulation can be set to run for up to 10,000 repetitions for combination of decision variables. We selected 1000 repetitions. Output is given for forecast cells. Figure 5.1 shows net profit for the combination of an ROP of 140 and a Q of 140.

Tabular output is also provided as in Table 5.2.

Similar output is given for the other forecast variable, SHORT (Fig. 5.2; Table 5.3).

Crystal Ball also provides a comparison over all decision variable values, as given in Table 5.4.

The implication here is that the best decision for the basic model parameters would be an ROP of 120 and a Q of 130, yielding an expected net profit of \$101,446 for the month. The shortage for this combination had a mean of 3.43 items per day, with a distribution shown in Fig. 5.3. The probability of shortage was 0.4385.

Table 5.1 Basic inventory model

	A	B	C	D	E	F	G	H	I	J	K
1	holdrate	0.8		ROP	140						
2	orderrate	300		Q	140						
3	purchase	90					net	110359.2		short	0
4	sell	130									
5							2440.8	6600	277200	388050	
6	day	Start	demand	Sales	end	order	holdcost	ordercost	purchase	revenue	SHORT
7	1	100	85	85	15	140	12	300	12600	11050	0
8	2	155	84	84	71	140	56.8	300	12600	10920	0
9	3	211	104	104	107	140	85.6	300	12600	13520	0
10	4	247	105	105	142	0	113.6	0	0	13650	0
11	5	142	104	104	38	140	30.4	300	12600	13520	0
12	6	178	116	116	62	140	49.6	300	12600	15080	0
13	7	202	105	105	97	140	77.6	300	12600	13650	0
14	8	237	94	94	143	0	114.4	0	0	12220	0
15	9	143	83	83	60	140	48	300	12600	10790	0
16	10	200	94	94	106	140	84.8	300	12600	12220	0
17	11	246	115	115	131	140	104.8	300	12600	14950	0
18	12	271	128	128	143	0	114.4	0	0	16640	0
19	13	143	107	107	36	140	28.8	300	12600	13910	0
20	14	176	110	110	66	140	52.8	300	12600	14300	0
21	15	206	102	102	104	140	83.2	300	12600	13260	0
22	16	244	96	96	148	0	118.4	0	0	12480	0
23	17	148	91	91	57	140	45.6	300	12600	11830	0
24	18	197	102	102	95	140	76	300	12600	13260	0
25	19	235	104	104	131	140	104.8	300	12600	13520	0

26	20	271	96	96	175	0	140	0	0	0	12480	0
27	21	175	103	103	72	140	57.6	300	12600	13390	0	0
28	22	212	98	98	114	140	91.2	300	12600	12740	0	0
29	23	254	97	97	157	0	125.6	0	0	12610	0	0
30	24	157	103	103	54	140	43.2	300	12600	13390	0	0
31	25	194	86	86	108	140	86.4	300	12600	11180	0	0
32	26	248	105	105	143	0	114.4	0	0	13650	0	0
33	27	143	89	89	54	140	43.2	300	12600	11570	0	0
34	28	194	106	106	88	140	70.4	300	12600	13780	0	0
35	29	228	89	89	139	140	111.2	300	12600	11570	0	0
36	30	279	84	84	195	0	156	0	0	10920	0	0

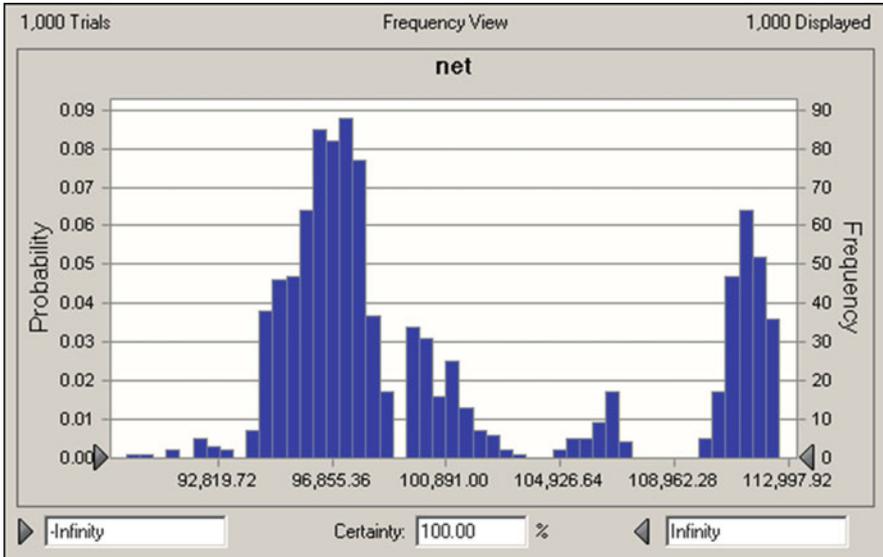


Fig. 5.1 Crystal ball output for net profit ROP 140, Q 140. ©Oracle. Used with permission

Table 5.2 Statistical output for net profit ROP 140, Q 140. ©Oracle. Used with permission

Forecast: net	
Statistic	Forecast values
Trials	1000
Mean	100,805.56
Median	97,732.8
Mode	97,042.4
Standard deviation	6264.80
Variance	39,247,672.03
Skewness	0.8978
Kurtosis	2.21
Coeff. of variability	0.0621
Minimum	89,596.80
Maximum	112,657.60
Mean Std. error	198.11

System Dynamics Modeling of Supply Chains

Many models contain variables that change continuously over time. One example would be a model of an oil refinery. The amount of oil moving between various stages of production is clearly a continuous variable. In other models, changes in variables occur gradually (though discretely) over an extended time period;

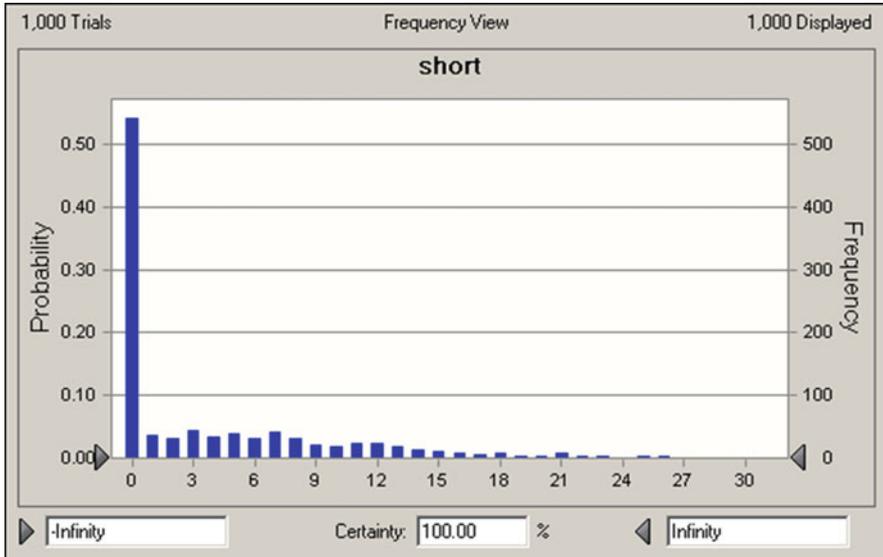


Fig. 5.2 SHORT for ROP 140, Q 140. ©Oracle. Used with permission

Table 5.3 Statistical output: ROP 140, Q 140

Forecast: net	
Statistic	Forecast values
Trials	1000
Mean	3.72
Median	0.00
Mode	0.00
Standard deviation	5.61
Variance	31.47
Skewness	1.75
Kurtosis	5.94
Coeff. of variability	1.51
Minimum	0.00
Maximum	31.00
Mean Std. error	0.18

however, for all intents and purposes, they may be treated as continuous. An example would be the amount of inventory at a warehouse in a production-distribution system over several years. As customer demand is fulfilled, inventory is depleted, leading to factory orders to replenish the stock. As orders are received from suppliers, the inventory increases. Over time, particularly if orders are relatively small and frequent as we see in just-in-time environments, the inventory level can be represented by a smooth, continuous, function.

Table 5.4 Comparative net profit for all values of ROP, Q. ©Oracle. Used with permission

	Trend Chart	Overlay Chart	Forecast Chart	Q (100.00)	Q (110.00)	Q (120.00)	Q (130.00)	Q (140.00)
ROP (80.00)				99,530	99,948	99,918	100,159	101,331
ROP (100.00)				99,627	100,701	101,051	101,972	101,512
ROP (120.00)				99,519	100,429	100,919	101,446	101,252
ROP (140.00)				99,525	99,894	100,586	100,712	100,805
				1	2	3	4	5

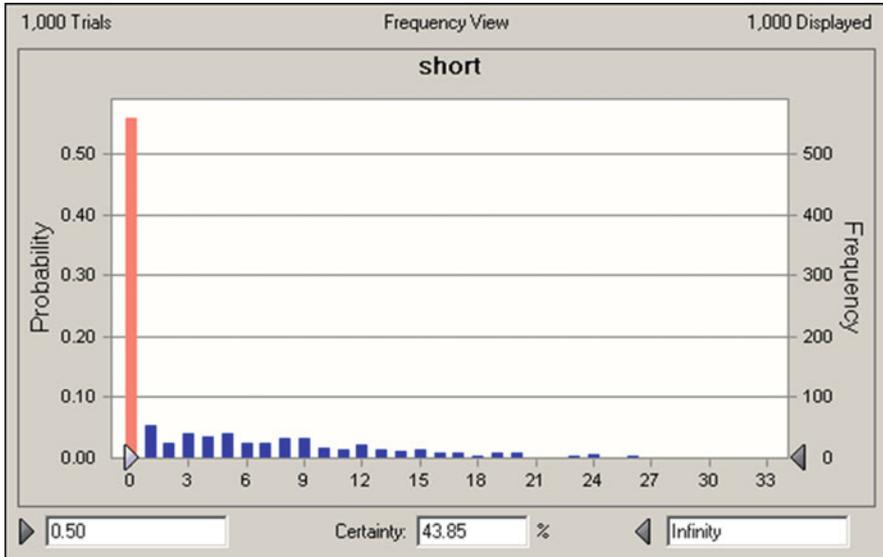


Fig. 5.3 SHORT for $R = 120$, $Q = 130$. ©Oracle. Used with permission

Continuous variables are often called state variables. A continuous simulation model defines equations for relationships among state variables so that the dynamic behavior of the system over time can be studied. To simulate continuous systems, we use an activity-scanning approach whereby time is decomposed into small increments. The defining equations are used to determine how the state variables change during an increment of time. A specific type of continuous simulation is called system dynamics, which dates back to the early 1960s and a classic work by Jay Forrester of M.I.T.¹ System dynamics focuses on the structure and behavior of systems that are composed of interactions among variables and feedback loops. A system dynamics model usually takes the form of an influence diagram that shows the relationships and interactions among a set of variables.

System dynamics models have been widely used to model supply chains, especially with respect to the bullwhip phenomenon,² which has to do with the dramatic increase in inventories across supply chains when uncertainty in demand appears. Many papers have dealt with the bullwhip effect through system dynamics models.³ These models have been used to evaluate lean systems,⁴ Kanban systems,⁵ and JIT systems.⁶ They also have been used to model vendor management inventory in supply chains.⁷

We present a four echelon supply chain model, consisting of a vendor providing raw materials, an assembly operation to create the product, a warehouse, and a set of five retailers. We will model two systems—one a push system, the other pull in the sense that upstream activity depends on downstream demand. We will present the pull system first.

	A	B	C	D	E
1	RevP	100	ROPven	20	
2	Cost	70	Qven	50	
3	Hold	1			
4		Vendor	Vendor		
5		Start	Prod	Send	End
6	Time				
7	1	40	=IF(E7<=\$D\$1,\$D\$2,0)	=IF(J7<=\$I\$1,\$D\$2,0)	=MAX(0,B7-D7)
8	=A7+1	=E7	=IF(E8<=\$D\$1,\$D\$2,0)	=IF(J8<=\$I\$1,\$D\$2,0)	=MAX(0,B8-D8)
9	=A8+1	=E8+C7	=IF(E9<=\$D\$1,\$D\$2,0)	=IF(J9<=\$I\$1,\$D\$2,0)	=MAX(0,B9-D9)
10	=A9+1	=E9+C8	=IF(E10<=\$D\$1,\$D\$2,0)	=IF(J10<=\$I\$1,\$D\$2,0)	=MAX(0,B10-D10)
11	=A10+1	=E10+C9	=IF(E11<=\$D\$1,\$D\$2,0)	=IF(J11<=\$I\$1,\$D\$2,0)	=MAX(0,B11-D11)
12	=A11+1	=E11+C10	=IF(E12<=\$D\$1,\$D\$2,0)	=IF(J12<=\$I\$1,\$D\$2,0)	=MAX(0,B12-D12)
13	=A12+1	=E12+C11	=IF(E13<=\$D\$1,\$D\$2,0)	=IF(J13<=\$I\$1,\$D\$2,0)	=MAX(0,B13-D13)
14	=A13+1	=E13+C12	=IF(E14<=\$D\$1,\$D\$2,0)	=IF(J14<=\$I\$1,\$D\$2,0)	=MAX(0,B14-D14)
15	=A14+1	=E14+C13	=IF(E15<=\$D\$1,\$D\$2,0)	=IF(J15<=\$I\$1,\$D\$2,0)	=MAX(0,B15-D15)
16	=A15+1	=E15+C14	=IF(E16<=\$D\$1,\$D\$2,0)	=IF(J16<=\$I\$1,\$D\$2,0)	=MAX(0,B16-D16)
17	=A16+1	=E16+C15	=IF(E17<=\$D\$1,\$D\$2,0)	=IF(J17<=\$I\$1,\$D\$2,0)	=MAX(0,B17-D17)
18	=A17+1	=E17+C16	=IF(E18<=\$D\$1,\$D\$2,0)	=IF(J18<=\$I\$1,\$D\$2,0)	=MAX(0,B18-D18)
19	=A18+1	=E18+C17	=IF(E19<=\$D\$1,\$D\$2,0)	=IF(J19<=\$I\$1,\$D\$2,0)	=MAX(0,B19-D19)
20	=A19+1	=E19+C18	=IF(E20<=\$D\$1,\$D\$2,0)	=IF(J20<=\$I\$1,\$D\$2,0)	=MAX(0,B20-D20)
21	=A20+1	=E20+C19	=IF(E21<=\$D\$1,\$D\$2,0)	=IF(J21<=\$I\$1,\$D\$2,0)	=MAX(0,B21-D21)
22	=A21+1	=E21+C20	=IF(E22<=\$D\$1,\$D\$2,0)	=IF(J22<=\$I\$1,\$D\$2,0)	=MAX(0,B22-D22)
23	=A22+1	=E22+C21	=IF(E23<=\$D\$1,\$D\$2,0)	=IF(J23<=\$I\$1,\$D\$2,0)	=MAX(0,B23-D23)
24	=A23+1	=E23+C22	=IF(E24<=\$D\$1,\$D\$2,0)	=IF(J24<=\$I\$1,\$D\$2,0)	=MAX(0,B24-D24)
25	=A24+1	=E24+C23	=IF(E25<=\$D\$1,\$D\$2,0)	=IF(J25<=\$I\$1,\$D\$2,0)	=MAX(0,B25-D25)
26	=A25+1	=E25+C24	=IF(E26<=\$D\$1,\$D\$2,0)	=IF(J26<=\$I\$1,\$D\$2,0)	=MAX(0,B26-D26)
27	=A26+1	=E26+C25	=IF(E27<=\$D\$1,\$D\$2,0)	=IF(J27<=\$I\$1,\$D\$2,0)	=MAX(0,B27-D27)
28	=A27+1	=E27+C26	=IF(E28<=\$D\$1,\$D\$2,0)	=IF(J28<=\$I\$1,\$D\$2,0)	=MAX(0,B28-D28)
29	=A28+1	=E28+C27	=IF(E29<=\$D\$1,\$D\$2,0)	=IF(J29<=\$I\$1,\$D\$2,0)	=MAX(0,B29-D29)
30	=A29+1	=E29+C28	=IF(E30<=\$D\$1,\$D\$2,0)	=IF(J30<=\$I\$1,\$D\$2,0)	=MAX(0,B30-D30)
31	=A30+1	=E30+C29	=IF(E31<=\$D\$1,\$D\$2,0)	=IF(J31<=\$I\$1,\$D\$2,0)	=MAX(0,B31-D31)
32	=A31+1	=E31+C30	=IF(E32<=\$D\$1,\$D\$2,0)	=IF(J32<=\$I\$1,\$D\$2,0)	=MAX(0,B32-D32)
33	=A32+1	=E32+C31	=IF(E33<=\$D\$1,\$D\$2,0)	=IF(J33<=\$I\$1,\$D\$2,0)	=MAX(0,B33-D33)
34	=A33+1	=E33+C32	=IF(E34<=\$D\$1,\$D\$2,0)	=IF(J34<=\$I\$1,\$D\$2,0)	=MAX(0,B34-D34)
35	=A34+1	=E34+C33	=IF(E35<=\$D\$1,\$D\$2,0)	=IF(J35<=\$I\$1,\$D\$2,0)	=MAX(0,B35-D35)
36	=A35+1	=E35+C34	=IF(E36<=\$D\$1,\$D\$2,0)	=IF(J36<=\$I\$1,\$D\$2,0)	=MAX(0,B36-D36)
37					=SUM(E7:E36)

Fig. 5.4 Factory model

Pull System

The basic model uses a forecasting system based on exponential smoothing to drive decisions to send material down the supply chain. We use EXCEL modeling, along with Crystal Ball software to do simulation repetitions, following Evans and Olson (2004).⁸ The formulas for the factory portion of the model are given in Fig. 5.4.

Figure 5.4 models a month of daily activity. Sales of products at retail generate \$100 in revenue for the core organization, at a cost of \$70 per item. Holding costs are \$1 at the retail level (\$0.50 at wholesale, \$0.40 at assembly, \$0.25 at vendors). Daily orders are shipped from each element, at a daily cost of \$1000 from factory to assembler, \$700 from assembler to warehouse, \$300 from warehouse to retailers. Vendors produce 50 items of material per day if inventory drops to 20 items or less. If not, they do not produce. They send material to the assembly operation if called by that element, which is modeled in Fig. 5.5 (only the first 5 days are shown). Vendor ending inventory is shown in column E, with cell E37 adding total monthly inventory.

The assembly operation calls for replenishment of 30 units from the vendor whenever their inventory of finished goods drops to 20 or less. Each daily delivery

10	4	=J9	=D9	=G9	=MIN(F10,M9)	=F10+H10-I10
11	5	=J10	=D10	=G10	=MIN(F11,M10)	=F11+H11-I11

Fig. 5.5 Core assembly model

	A	K	L	M	N	O	P
1				WholMin	20		
2				WholMax	25		
3							
4		Whol					
5	Day	Start	Demand	Order	End	Short	Sent
6				0			
7	1	=20	=20	=IF(O7>0,\$N\$1+INT(0.7*O7),IF(N7>\$N\$2.0,\$N\$2-N7))	=K7-P7	=IF(L7>K7,L7-K7,0)	MIN(K7,L7)
8	2	=N7+I7	=T7+Y7+AD7+AI7+AM7	=IF(O8>0,\$N\$1+INT(0.7*O8),IF(N8>\$N\$2.0,\$N\$2-N8))	=K8-P8	=IF(L8>K8,L8-K8,0)	MIN(K8,L8)
9	3	=N8+I8	=T8+Y8+AD8+AI8+AM8	=IF(O9>0,\$N\$1+INT(0.7*O9),IF(N9>\$N\$2.0,\$N\$2-N9))	=K9-P9	=IF(L9>K9,L9-K9,0)	MIN(K9,L9)
10	4	=N9+I9	=T9+Y9+AD9+AI9+AM9	=IF(O10>0,\$N\$1+INT(0.7*O10),IF(N10>\$N\$2.0,\$N\$2-N10))	=K10-P10	=IF(L10>K10,L10-K10,0)	MIN(K10,L10)
11	5	=N10+I10	=T10+Y10+AD10+AI10+AM10	=IF(O11>0,\$N\$1+INT(0.7*O11),IF(N11>\$N\$2.0,\$N\$2-N11))	=K11-P11	=IF(L11>K11,L11-K11,0)	MIN(K11,L11)

Fig. 5.6 Wholesale model

is 30 units, and is received at the beginning of the next day’s operations. The assembly operation takes one day, and goods are available to send that evening. Column J shows ending inventory to equal what starting inventory plus what was processed that day minus what was sent to wholesale. Figure 5.6 shows the model of the wholesale operation.

The wholesale operation feeds retail demand, which is shown in column L. They feed retailers up to the amount they have in stock. They order from the assembler if they have less than 25 items. If they stock out, they order 20 items plus 70 % of what they were unable to fill (this is essentially an exponential smoothing forecast). If they still have stock on hand, the order to fill up to 25 items. Figure 5.7 shows one of the five retailer operations (the other four are identical).

Retailers face a highly variable demand with a mean of 4. They fill what orders they have stock for. Shortfall is measured in column U. They order if their end-of-day inventory falls to 4 or less. The amount ordered is 4 plus 70 % of shortfall, up to a maximum of 8 units.

This model is run of Crystal Ball to generate a measure of overall system profit. Here the profit formula is \$175 times sales minus holding costs minus transportation costs. Holding costs at the factory were \$0.25 times sum of ending inventory, at the assembler \$0.40 times sum of ending inventory, at the warehouse 0.50 times ending inventory, and at the retailers \$1 times sum of ending inventories. Shipping costs were \$1000 per day from factory to assembler, \$700 per day from assembler to warehouse, and \$300 per day from warehouse to retailer. The results of 1000 repetitions are shown in Fig. 5.8.

Here average profit for a month is \$5942, with a minimum a loss of \$8699 and a maximum a gain of \$18,922. There was a 0.0861 probability of a negative profit. The amount of shortage across the system is shown in Fig. 5.9. The average was 138.76, with a range of 33 to 279 over the 1000 simulation repetitions.

	A	Q	R	S	T	U
1		start	4		order	ROP+.7short
2		rop	4			to Tmax
3		Tmax	8			
4						
5		R1				
6		start	demand	end	order	short
7		=SR\$1	=INT(CB.Exponential(0.25))	=MAX(0,Q7-R7)	=IF(S7<=\$R\$2.4+INT(0.7*U7),IF(S7>\$R\$3.0,\$R\$3-S7))	=IF(R7>Q7,R7-Q7,0)
8		=S7+MIN(P7,T7)	=INT(CB.Exponential(0.25))	=MAX(0,Q8-R8)	=IF(S8<=\$R\$2.4+INT(0.7*U8),IF(S8>\$R\$3.0,\$R\$3-S8))	=IF(R8>Q8,R8-Q8,0)
9		=S8+MIN(P8,T8)	=INT(CB.Exponential(0.25))	=MAX(0,Q9-R9)	=IF(S9<=\$R\$2.4+INT(0.7*U9),IF(S9>\$R\$3.0,\$R\$3-S9))	=IF(R9>Q9,R9-Q9,0)
10		=S9+MIN(P9,T9)	=INT(CB.Exponential(0.25))	=MAX(0,Q10-R10)	=IF(S10<=\$R\$2.4+INT(0.7*U10),IF(S10>\$R\$3.0,\$R\$3-S10))	=IF(R10>Q10,R10-Q10,0)
11		=S10+MIN(P10,T10)	=INT(CB.Exponential(0.25))	=MAX(0,Q11-R11)	=IF(S11<=\$R\$2.4+INT(0.7*U11),IF(S11>\$R\$3.0,\$R\$3-S11))	=IF(R11>Q11,R11-Q11,0)

Fig. 5.7 Retailing model

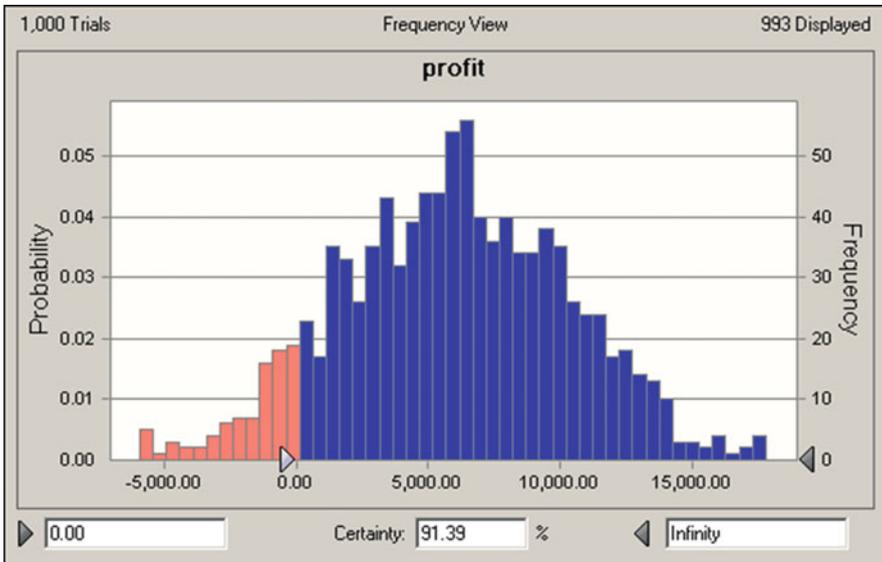


Fig. 5.8 Overall system profit for basic model. ©Oracle. Used with permission

The central limit theorem can be shown to have effect, as the sum of the five retailer shortfalls has a normally shaped distribution. Figure 5.10 shows shortfall at the wholesale level, which had only one entity.

The average wholesale shortages was 15.73, with a minimum of 0 and a maximum of 82. Crystal Ball output indicates a probability of shortfall of 0.9720, meaning a 0.0280 probability of going the entire month without having shortage at the wholesale level.

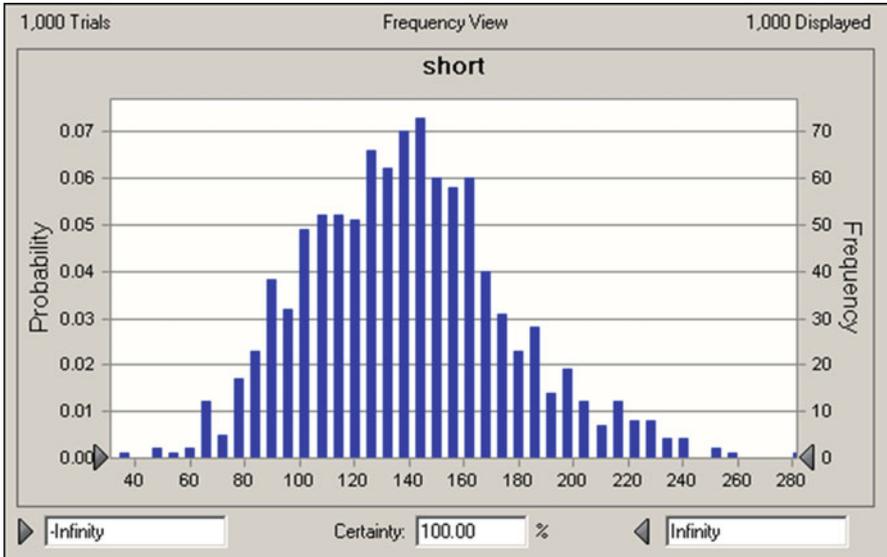


Fig. 5.9 Retail shortages for basic model. ©Oracle. Used with permission

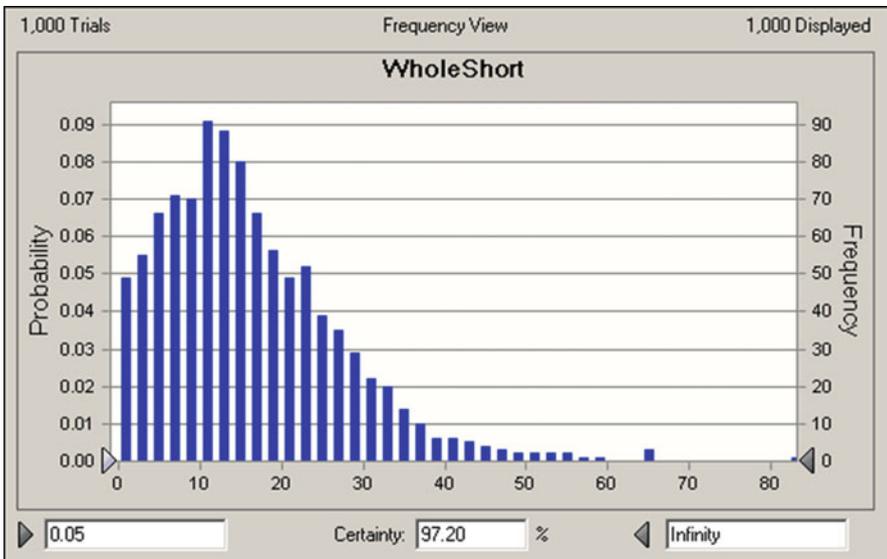


Fig. 5.10 Wholesale shortages for basic model. ©Oracle. Used with permission

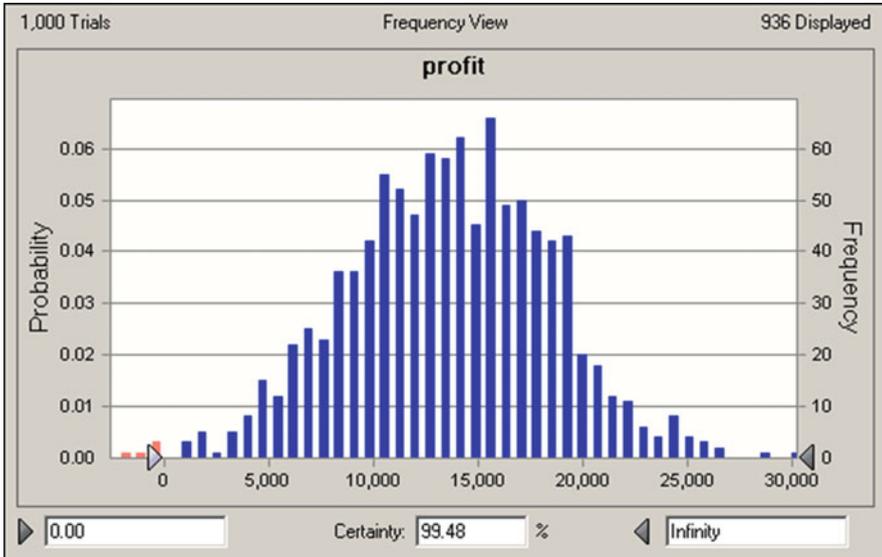


Fig. 5.11 Push system profit. ©Oracle. Used with permission

Push System

The difference in this model is that production at the factory (column C in Fig. 5.4) is a constant 20 per day, the amount sent from the factory to the assembler (column D in Fig. 5.4) is also 20 per day, the amount ordered by the wholesaler (column M in Fig. 5.6) is 20, the amount sent by the wholesaler to retailers (column P in Fig. 5.6) is a constant 20, and the amount ordered by the wholesaler (column T in Fig. 5.7) is a constant 20.

This system proved to be more profitable and safer for the given conditions. Profit is shown in Fig. 5.11.

The average profit was \$13,561, almost double that of the more variable push system. Minimum profit was a loss of \$2221, with the probability of loss 0.0052. Maximum profit was \$29,772. Figure 5.12 shows shortfall at the retail level.

The average shortfall was only 100.32, much less than the 137.16 for the pull model. Shortfall at the wholesale level (Fig. 5.13) was an average of 21.54, ranging from 0 to 67.

For this set of assumed values, the push system performed better. But that establishes nothing, as for other conditions, and other means of coordination, a pull system could do better.

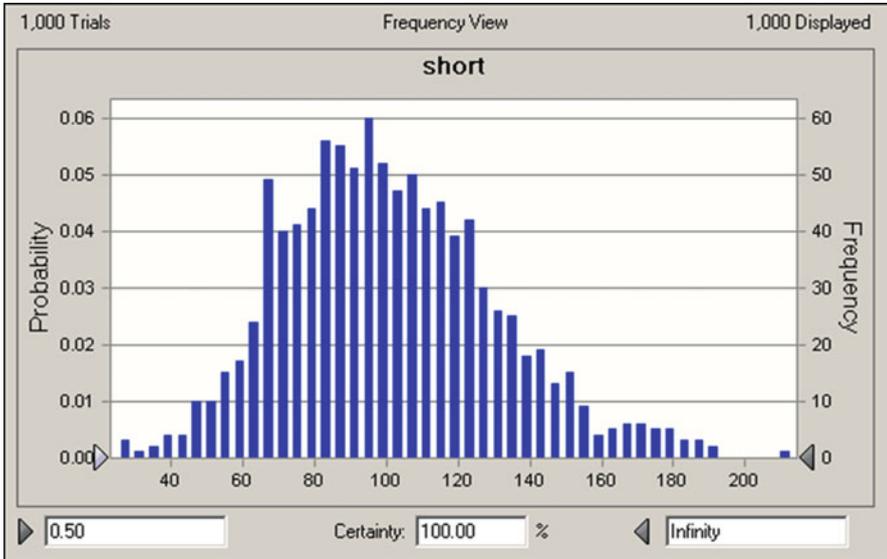


Fig. 5.12 Retail shortages for the push model. ©Oracle. Used with permission

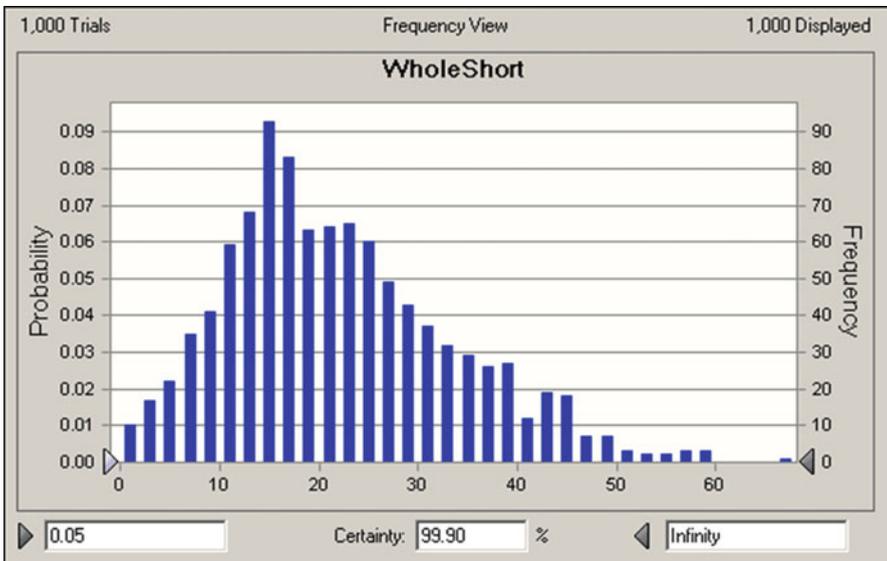


Fig. 5.13 Wholesale shortages for the push model. ©Oracle. Used with permission

Monte Carlo Simulation for Analysis

Simulation models are sets of assumptions concerning the relationship among model components. Simulations can be time-oriented (for instance, involving the number of events such as demands in a day) or process-oriented (for instance, involving queuing systems of arrivals and services). Uncertainty can be included by using probabilistic inputs for elements such as demands, inter-arrival times, or service times. These probabilistic inputs need to be described by probability distributions with specified parameters. Probability distributions can include normal distributions (with parameters for mean and variance), exponential distributions (with parameter for a mean), lognormal (parameters mean and variance), or any of a number of other distributions. A simulation run is a sample from an infinite population of possible results for a given model. After a simulation model is built, the number of trials is established. Statistical methods are used to validate simulation models and design simulation experiments.

Many financial simulation models can be accomplished on spreadsheets, such as Excel. There are a number of commercial add-on products that can be added to Excel, such as @Risk or Crystal Ball, that vastly extend the simulation power of spreadsheet models. These add-ons make it very easy to replicate simulation runs, and include the ability to correlate variables, expeditiously select from standard distributions, aggregate and display output, and other useful functions.

In supply chain outsourcing decisions, a number of factors can involve uncertainty, and simulation can be useful in gaining better understanding of systems.⁹ We begin by looking at expected distributions of prices for the component to be outsourced from each location. China C in this case has the lowest estimated price, but it has a wide expected distribution of exchange rate fluctuation. These distributions will affect the actual realized price for the outsourced component. The Chinese C vendor is also rated as having relatively high probabilities of failure in product compliance with contractual standards, in vendor financial survival, and in political stability of host country. The simulation is modeled to generate 1000 samples of actual realized price after exchange rate variance, to include having to rely upon an expensive (\$5 per unit) price in case of outsourcing vendor failure.

Monte Carlo simulation output is exemplified in Fig. 5.14, which shows the distribution of prices for the hypothetical Chinese outsourcing vendor C, which was the low price vendor very nearly half of the time. Figure 5.15 shows the same for the Taiwanese vendor, and Fig. 5.16 for the safer but expensive German vendor.

The Chinese vendor C has a higher probability of failure (over 0.31 from all sources combined, compared to 0.30 for Indonesia). This raises its mean cost, because in case of failure, the \$5 per unit default price is used. There is a cluster around the contracted cost of \$0.60, with a minimum dropping slightly below 0 due to exchange rate variance, a mean of \$0.78 and a maximum of \$1.58 given survival in all three aspects of risk modeled. There is a spike showing a default price of \$5.00 per unit in 0.3134 of the cases. Thus while the contractual price is lowest for this alternative, the average price after consideration of failure is \$2.10.

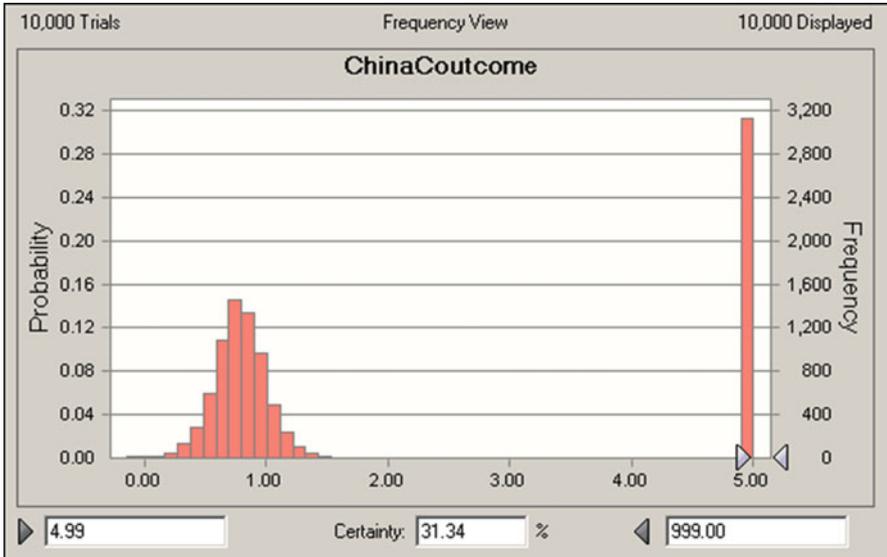


Fig. 5.14 Distribution of results for Chinese vendor C costs. ©Oracle. Used with permission

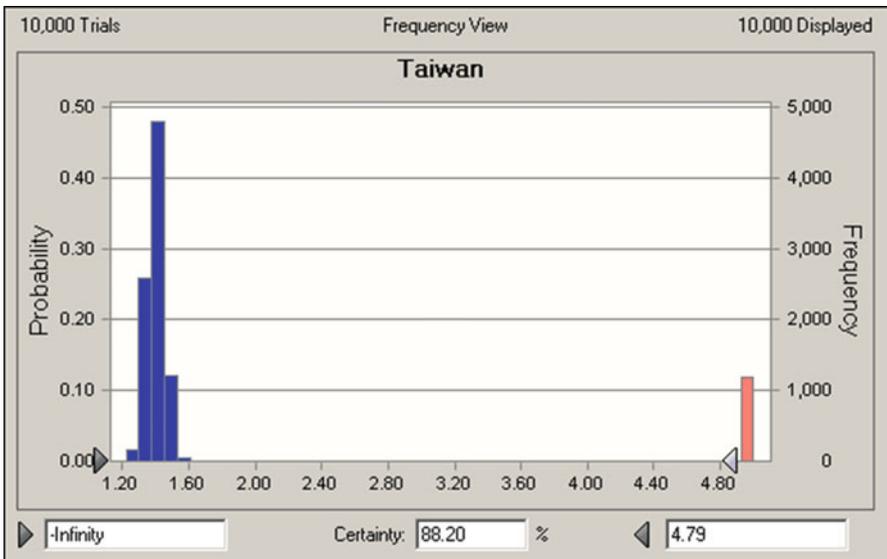


Fig. 5.15 Distribution of results for Taiwanese vendor costs. ©Oracle. Used with permission

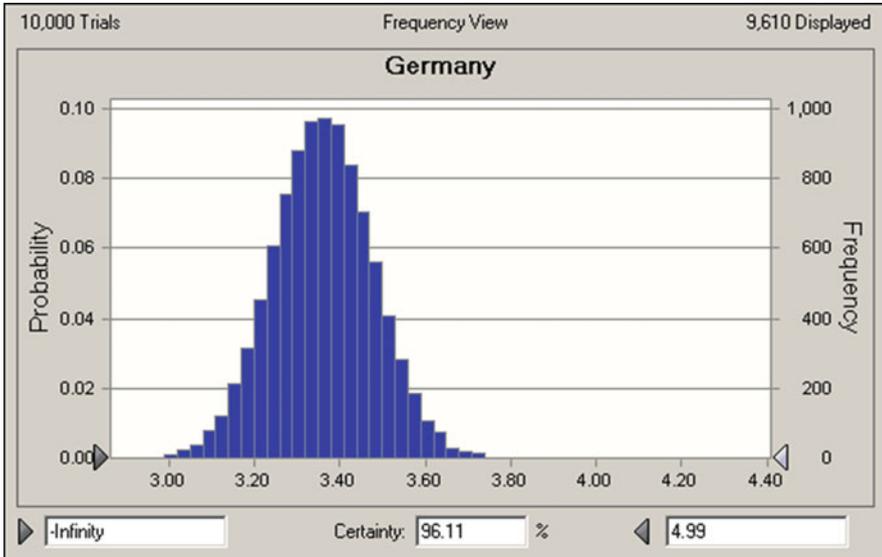


Fig. 5.16 Distribution of results for Germany vendor costs. ©Oracle. Used with permission

Table 5.5 Simulation output

Vendor	Mean Cost	Min Cost	Max Cost	Probability of Failure	Probability Low	AvgCost if didn't fail	Average overall
China B	0.70	- 0.01	1.84	0.2220	0.1370	0.91	1.82
Taiwan	1.36	1.22	1.60	0.1180	0.0033	1.41	1.83
China C	0.60	0.05	1.58	0.3134	0.4939	0.78	2.10
China A	0.82	- 0.01	2.16	0.2731	0.0188	1.07	2.14
Indonesia	0.80	0.22	1.61	0.2971	0.1781	0.96	2.16
Arizona	1.80	1.80	1.80	0.2083	0.0001	2.71	2.47
Vietnam	0.85	0.40	1.49	0.3943	0.1687	0.94	2.54
Alabama	2.05	2.05	2.05	0.2472	0		2.78
Ohio	2.50	2.50	2.50	0.2867	0		3.22
Germany	3.20	2.90	3.81	0.0389	0		3.42

Note: Average Overall assumes cost of \$5 to Supply Chain should Vendor Fail

Table 5.5 shows comparative output. Simulation provides a more complete picture of the uncertainties involved.

Probabilities of being the low-cost alternative are also shown. The greatest probability was for China C at 0.4939, with Indonesia next at 0.1781. The expensive (but safer) alternatives of Germany and Alabama both were never low (and thus were dominated in the DEA model). But Germany had a very high probability of survival, and in the simulation could appear as the best choice (rarely).

Conclusion

Simulation is the most flexible management science modeling technique. It allows making literally any assumption you want, although the trade-off is that you have to work very hard to interpret results in a meaningful way relative to your decision.

Because of the variability inherent in risk analysis, simulation is an obviously valuable tool for risk analysis. There are two basic simulation applications in business. Waiting line models involve queuing systems, and software such as Arena (or many others) are very appropriate for that type of modeling. The other type is supportable by spreadsheet tools such as Crystal Ball, demonstrated in this chapter. Spreadsheet simulation is highly appropriate for inventory modeling as in push/pull models. Spreadsheet models also are very useful for system dynamic simulations. We will see more Crystal Ball simulation models in chapters covering value at risk and chance constrained models.

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