Chapter 7

Simulation Modeling and Analysis of Integrated Supply Chain Network Configurations

7.1 A Component based Simulation Modeling Approach

From a system perspective, a supply chain process consists of the flow of materials, information and services, and the monitoring and control of these flows. Typical activities include: raw material procurement, inventory management, order processing, warehousing, transportation, distribution and production. Supply chain management is concerned with the development of functions to support these activities.

Several methods to develop a model of a system have been proposed. Top down development starts with a model at a high abstraction level, this model is refined by a number of disaggregation (or decomposition) steps until the desired level of detail has been reached. Bottom up development starts with some subsystems that are detailed descriptions of some aspect or part of the systems. Then, these sub-models are composed into a model of the entire system. In this research, a mixture of top down and bottom up development is employed to build a model.

Practical experiences show that some supply chain networks have subsystems that have a lot in common. For example, a distribution center and a production unit have transportation subsystems for internal transport. To support the modeling process it is useful to reuse some typical subsystems, often called *components* or *building blocks*. Reusing these components reduces the modeling effort. And, from these reusable components, the rapid reconfiguration of a supply chain network can be achieved.

Some requirements on the components include: (1) they can be parameterized, which make them tailored for a specific situation; (2) they have to be robust in the sense that it can handle various inputs, i.e. the number of assumptions about the environment of the component is as few as possible.

Some typical components in a supply chain network are given as follows:

- Raw material supplier: the beginning of the chain
- Production unit: the manufacturing of goods (transforming, assembling, splitting up)
- Distribution center: the rearrangement and the distribution of goods
- Transportation center: the transportation of goods
- Consumer: the end of the chain

7.2 Stroboscope — A State and Resource based Simulation Language

STROBOSCOPE is a general-purpose discrete-event simulation language based on activity scanning and activity cycle diagrams (ACDs). A subset of the STROBOSCOPE modeling concepts are directly analogous to those used in timed stochastic colored Petri-nets, but use a different terminology (token=resource; place=queue; transition=activity; arc=link).

STROBOSCOPE tokens can be colored with any number of properties and methods. The entire state of the model (e.g., number of tokens in a place, number of times a transition has fired) and the colors of tokens are accessible via variables. Arcs can enable transition firing based on the truth of any expression; allowing arcs to be inhibitors, activators, or to take on any other role. Transition timing can be defined with any valid expression (functions that sample from various probability distributions are available). STROBOSCOPE also includes many powerful extensions not found in Petri-nets (Martinez 1996).

7.2.1 Network Elements

7.2.1.1 Resources

Resources are things required to perform tasks. These can be machinery, space, materials, labor, permits, or anything else needed to perform a particular task.

The most important characteristic of a resource is its type. The type of a resource places the resource within a category of resources that share common traits or characteristics.

7.2.1.2 Queues

Queues are nodes in which resources spend time passively (they are either stored there, or waiting to be used). Each queue is associated with a particular resource type. Queues that hold discrete resources have attributes that control the ordering of the individual resources within the Queue.

7.2.1.3 Activities

Activities are nodes that represent work or tasks to be performed using the necessary resources. Resources spend time in activities actively (performing a task). Resources involved in activities are productive, sometimes in collaboration with other resources.

Combi activities: represent tasks that start when certain conditions are met.

Normal activities: represent tasks that start immediately after other tasks end. Among all nodes in a network, only activity instances represent tasks that end and release resources. For this reason, only other activities can be predecessors to a *Normal Activity*.

7.2.1.4 Links

Links connect network nodes and indicate the direction and type of resources that flow through them. Links have many attributes that can be used to control the flow of resources from the predecessor node to the successor node.

7.3 Some Building Blocks for Simulation Modeling of Supply Chain Networks

Basically, the following generic building blocks can be found in the supply chain networks: (1) a supplier component; (2) a distribution center component; (3) transportation components; (4) a factory component; (5) a consumer component; and (6) a replenishment component.

In the following, STROBOSCOPE is used as a tool to build some generic components for supply chain simulation modeling.

7.3.1 The Retailers

7.3.1.1 Statistical Considerations on Customer Demands

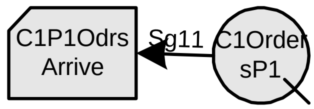

Figure 7.1 The modeling block for customer demands

The normal, Poisson, and negative exponential distributions have been found to be of considerable value in describing demand functions. The normal distribution has been found to describe many demand functions at the factory level; the Poisson, at the retail level; and the negative exponential, at the wholesale and retail level. When dealing with a relatively low stochastic demand it is usually assumed that the demand process is Poisson. Besides, it is in many situations a quite realistic assumption. In this research, Poisson distribution is adopted to model the arrivals of customer demands.

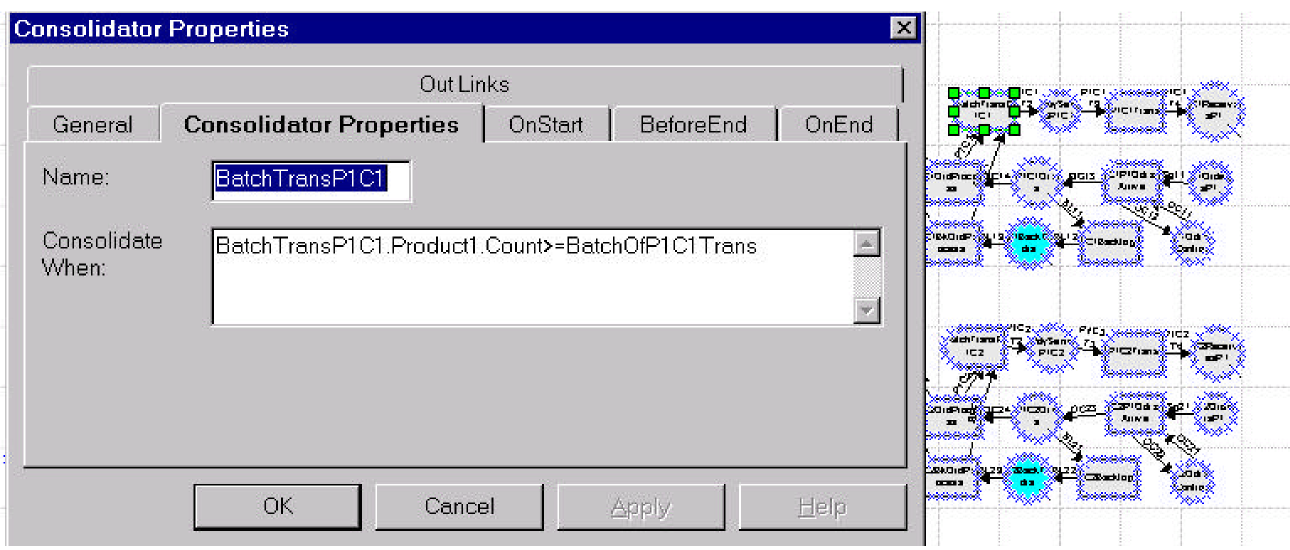

Figure 7.2 The snapshot for “Consolidator Properties of BatchTransP1C1”

For example, the arrival of customer orders (see Figure 7.1) can be modeled with the following code:

```
/ Assume that their inter-arrival rate is 12 minutes (5 per hour)
SEMAPHORE C1P1OdrsArrive !C1P1OdrsArrive.CurInst;  / one at a time
DURATION C1P1OdrsArrive Exponential[12];
BEFOREEND C1P1OdrsArrive GENERATE 1 PT1Orders; / generate a order
```

The corresponding snapshot for “Consolidator Properties of BatchTransP1C1” is shown in Figure 7.2.

7.3.2 The Warehouses

7.3.2.1 Replenishment Lead Time

The lead time to replenish the central warehouse is assumed to be either a constant or a stochastic variable with a given distribution. The retailer replenishment lead times are always stochastic due to occasional stock-outs at the central warehouses. Given that the warehouse has stock on hand, the lead time (transportation time) may be constant or stochastic. Since there is no direct customer demand at the warehouse, there are no costs or constraints associated with shortages there. Such shortage will, however, delay deliveries to the retailers and in that way have an impact on customer service.

Backorders at all locations are filled on a first-come-first-serve basis. This is not necessarily most economical but simplifies the analysis and is also, in a sense, a fair policy.

7.4 Approximate Inventory Analysis for Multi-Echelon Distribution Systems

Although there are many controllable variables in the simulation study of supply chain networks, we are only interested in some key factors such as safety stock level and reorder point at different stages. To facilitate the analysis of simulation models, it is necessary to provide the estimated values for other non-key variables. In the following, the approximate inventory analysis for multi-echelon distribution systems is given.

Inventory management in multi-echelon distribution systems is complex because demand at the central warehouse is dependent on the demand and stocking decisions at the branch warehouses. And demand at the branches is dependent on the demand and stocking decisions at the retail outlets. For a one-warehouse, n-retailer situation with $n \geq 3$, literature shows that the form of the optimal policy can be very complex (Graves et al. 1993); in particular, it requires that the order quantity at one or more of the locations vary with time even though all relevant demand and cost factors are time-invariant. But researchers rightfully argue for restricting attention to a simpler class of strategies (where each location's order quantity does not change with time) and develop an effective heuristic for finding quite good solutions.

Because multi-echelon models examine the entire system, they might recommend holding just a few parts at the warehouse level, and none at the retailers. System-wide savings can be enormous. With faster moving parts, it is likely that more units would be held at the retail level, but multi-echelon methods help determine how many to hold at the retailers, and how many to hold at the warehouse. It is intuitive that using multi-echelon inventory techniques will provide a significant benefit over using the single-stage models in a multi-level setting. Moreover, these multi-echelon techniques have been successfully implemented.

7.4.1 Echelon Stock and Installation Stock Policies for Multi-Echelon Distribution Systems

A multi-level inventory system is often controlled either by an installation stock reorder point policy or by an echelon stock reorder point policy. An *installation stock policy* means that ordering decisions at each installation are based exclusively on the inventory position at this installation. Here, *inventory position* means the stock on hand and on order minus the backlog. When using an echelon stock policy, ordering decisions at each installation are instead based on the echelon inventory position. The *echelon inventory position* is obtained by adding the installation inventory positions at the installation and all its down-stream installations. It is previously known that echelon stock policies dominate installation stock reorder point policies for serial and assembly multi-level inventory systems. Depending on the structure of the distribution systems, either echelon stock or installation stock policies may be advantageous.

7.4.2 Sequential Stocking Points with Level Demand

7.4.2.1 Analytic Results

Some preliminary notations are given in the following:

D = deterministic, constant demand rate at the retailer, in units/unit time

A_w = fixed (setup) cost associated with a replenishment at the warehouse, in dollars

A_R = fixed (setup) cost associated with a replenishment at the retailer, in dollars

v_w = unit variable cost or value of the item at the warehouse, in \$/unit

v_R = unit variable cost or value of the item at the retailer, in \$/unit

r = carrying charge, in \$/\$/unit time

Q_w = replenishment quantity at the warehouse, in units

Q_R = replenishment quantity at the retailer, in units

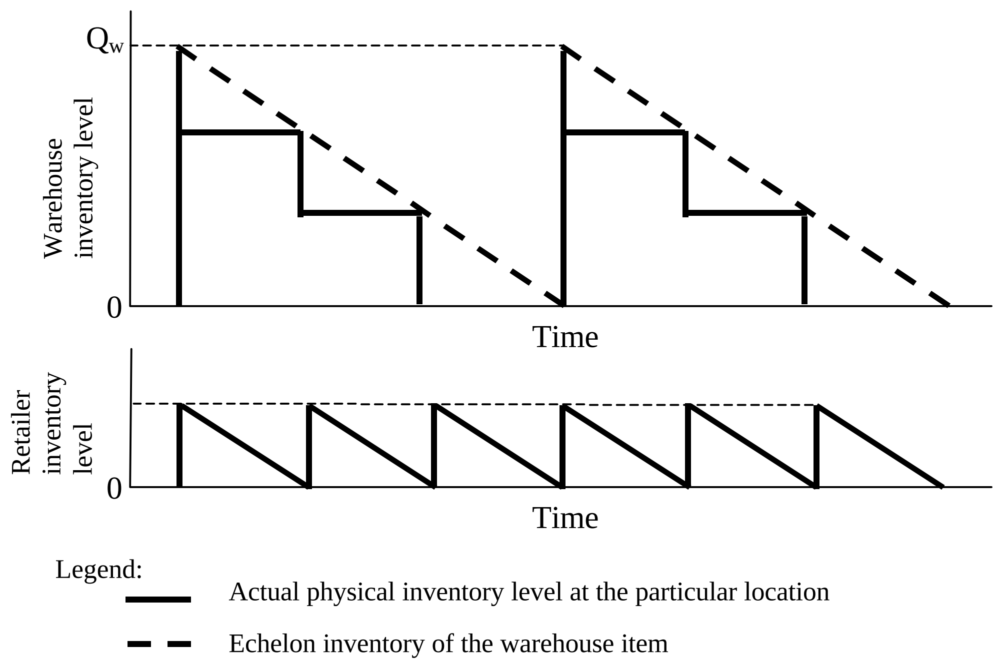

Figure 7.3 Behavior of the inventory levels in a deterministic two-stage distribution system

Figure 7.3 shows the behavior of the two levels of inventory with the passage of time for the particular case where $Q_w = 3Q_R$. This graph shows that at least for the case of deterministic demand it never would make sense to have Q_w be anything but an integer multiple of Q_R. Therefore, we have:

$$Q_w = nQ_R \qquad\qquad n = 1, 2, 3, \ldots$$

Note that, from Figure 7.3, the inventory at the warehouse does not follow the usual saw-tooth pattern, even though the end usage is deterministic and constant with time. The reason is that the withdrawals from the warehouse inventory are of size Q_R. We could use the conventional inventory definitions to analyze the system. However, the determination of average inventory levels becomes complicated. Instead, it is easier to use the echelon stock concept. With uniform end-item demand, each echelon stock has a saw-tooth pattern with time, as shown in Fig. 7.3. Thus, it is simple to compute the average value of an echelon stock.

Since the same physical units of stock can appear in more than one echelon inventory, we cannot simply multiply each average echelon stock by the standard *vr* term and sum to obtain total inventory carrying costs. A solution to the problem is to value any specific echelon inventory at only the value added at that particular echelon. When the decision being made is whether to store inventory at an upstream location or at a downstream location that it supplies, the relevant holding cost is the incremental cost of moving the product to the retailer. This incremental cost is exactly the echelon holding cost. Thus, in a two-stage distribution system, the warehouse echelon inventory is valued at $v'_w = v_w$, while the retailer echelon inventory is valued at only $v'_R = v_R - v_w$. More generally, in a production assembly context the echelon valuation v' at a particular stage i is given by $v'_i = v_i - \sum v_j$, where the summation is over all immediate predecessors, j.

For two-stage serial situation, the total costs (setup plus carrying) per unit time are given by

$$TC(Q_W, Q_R) = \frac{A_W D}{Q_W} + \bar{I}'_W \cdot v'_w \cdot r + \frac{A_R D}{Q_R} + \bar{I}'_R \cdot v'_R \cdot r \tag{7-1}$$

where

$\bar{I}'_W$ = average value of the warehouse echelon inventory, in units

$\bar{I}'_R$ = average value of the retailer echelon inventory, in units

Substituting $Q_w = nQ_R$ and noting that the echelon stocks follow saw-tooth patterns,

$$TC(nQ_R, Q_R) = \frac{A_W D}{nQ_R} + \frac{nQ_R \cdot v'_w \cdot r}{2} + \frac{A_R D}{Q_R} + \frac{Q_R \cdot v'_R \cdot r}{2}$$

$$= \frac{D}{Q_R}\left(A_R + \frac{A_W}{n}\right) + \frac{Q_R \cdot r}{2}\left(nv'_W + v'_R\right) \qquad (7\text{-}2)$$

A convenient approach is to first set the partial derivative of *TC* with respect to Q_R equal to zero and solve for the associated $Q^*_R(n)$.

$$Q^*_R(n) = \sqrt{\frac{2\left[A_R + \frac{A_W}{n}\right]D}{\left(nv'_W + v'_R\right)\cdot r}} \qquad (7\text{-}3)$$

Then,

$$TC^*(n) = \sqrt{2\left[A_R + \frac{A_W}{n}\right]D\left(nv'_W + v'_R\right)\cdot r} \qquad (7\text{-}4)$$

The value of *n* that minimizes $TC^*(n)$ also minimizes the following expression

$$F(n) = \left[A_R + \frac{A_W}{n}\right]\left(nv'_W + v'_R\right) \qquad (7\text{-}5)$$

From $\frac{dF(n)}{dn} = 0$, we know

$$\left[-\frac{A_W}{n^2}\right]\left(nv'_w + v'_R\right) + \left[A_R + \frac{A_W}{n}\right]v'_w = 0 \qquad (7\text{-}6)$$

Therefore,

$$n^* = \sqrt{\frac{A_W v'_R}{A_R v'_w}} \qquad (7\text{-}7)$$

7.4.2.2 Numerical Illustration

Let us consider a distribution system that consists of warehouse and retailers. The demand for the product can be assumed to be essentially deterministic and level at 210 units per year. The unit value of the product at the warehouse, v'_{w} or v_{w}, is \$1/unit, while the value added by considering the transportation cost, $v'_{\mathrm{R}} = v_{\mathrm{R}} - v_{\mathrm{w}}$, is \$4/unit. The fixed component of the purchase charge (A_w) is \$10, while the setup cost for ordering (A_R) at retailers is \$15. Finally, the estimated carrying charge is 2 \$/\$/year.

Solution: Step 1

$$n^* = \sqrt{\frac{(10)(4)}{(15)(1)}} = 1.63$$

Step 2

$n_1=1$ and $n_2=2$

Step 3

F(1) = [15+10/1][1+4] =125

F(2) = [15+10/2][(2)(1)+4] =120

Since F(1)>F(2), we use n = 2.

Step 4

$$Q_R = \sqrt{\frac{2\left[15+\frac{10}{2}\right](210)}{\left[(2)(1)+4\right]\cdot 2}} = 26.45 \approx 26 \text{ units}$$

Step 5

$Q_w = (2)(26) = 52$ units

7.4.3 Lead Time Demand and Re-Order Points Calculation for Serial Situation

7.4.3.1 Analytic Results

Some assumptions and preliminary notations are given in the following:

(1) External demand occurs only at the retailer and is a stationary process.

(2) Deterministic lead time associated with each stage and the lead time means the time period when the warehouse has stock on hand.

(3) Use of continuous review policy, i.e., (r, Q) form.

r_w = reorder point (based on the echelon inventory position) at the warehouse

Q_w = replenishment quantity at the warehouse ($Q_w = nQ_R$), in units

r_R = reorder point at the retailer

Q_R = replenishment quantity at the retailer, in units

Note that the restriction, $Q_w = nQ_R$, implies that the policies are *nested*: when the warehouse orders the retailer also orders. This policy is necessarily nested because the warehouse's inventory position changes only when the retailer orders. The nested policy means that a replenishment cannot occur at an operation unless one also occurs at immediate successor operations.

The reorder point at the retailer can be expressed as follows:

$$r_R = \hat{x}_{L_R} + k_R s_{L_R} \tag{7-8}$$

where

$\hat{x}_{L_R}$ = expected forecast demand over a retailer lead time

s_{L_R} = standard deviation of forecast errors over a retailer lead time

k_R = retailer safety factor, which satisfies

$$p_{u\geq}(k_R) = \frac{Q_R(v_R - v_w)r}{B_2 v_R D} \tag{7-9}$$

where B_2 is the fraction of unit value charged per unit short;

$G_u(k) = \int_k^\infty (u_0 - k)\frac{1}{\sqrt{2p}}\exp(-u_0^2/2)du_0$ is a special function of the unit normal (mean 0, standard deviation 1) variable. $G_u(k)$ is used in finding the expected shortages per replenishment cycle;

$p_{u^3}(k)$ = probability that a unit normal variable takes on a value of k or larger. $p_{u^3}(k)$ is often expressed as 1- $\Phi(k)$, where $\Phi(k)$ is the cumulative distribution function (or the left tail) of the unit normal evaluated at k (Silver, Pyke, and Peterson, 1998).

Similarly, the reorder point at the warehouse can be expressed as follows:

$$r_w = \hat{x}_{L_W + L_R} + k_w s_{L_W + L_R} \tag{7-10}$$

where

$\hat{x}_{L_W + L_R}$ = expected demand over a warehouse lead time and retailer lead time

$s_{L_W + L_R}$ = standard deviation of forecast errors over a warehouse lead time and retailer lead time

k_w = warehouse safety factor, which satisfies

$$p_{u\geq}(k_w) = \frac{Q_R[v_R + (n-1)v_w]r}{B_2 v_R D} \tag{7-11}$$

The L_w+L_R combination occurs in Eq. (7-10) because on every nth replenishment at the retailer there is an associated warehouse replenishment, and the latter should be initiated when there is sufficient echelon stock to protect against shortages over a period of length L_w+L_R.

7.4.3.2 Numerical Illustration

The same example in previous section is used here. Suppose that the transportation lead time for retailer is 2 weeks (or 80 hours) and the transportation lead time for warehouse is 1 week (or 40 hours). Also, assume that forecast errors are normally distributed, with the s for one week being 0.8 units, and that $s_t = \sqrt{t} s_1$. Finally, suppose that the fractional charge per unit short, B_2, is set at \$2.9.

From Eq. (7-9), we obtain

$$p_{u\geq}(k_R) = \frac{(26)(5-1)(2)}{(2.9)(5)(210)} = 0.0683$$

Then, from Table B.1 in Appendix B (Silver, Pyke, and Peterson, 1998), we have

$$k_R = 1.49$$

Consequently, from Eq. (7-8)

$$r_R = \frac{2}{52}(210) + 1.49 \cdot (\sqrt{2})(0.8) = 9.763, \text{ say 10 units}$$

From Eq. (7-11), we have

$$p_{u\geq}(k_w) = \frac{(26)[5+(2-1)(1)](2)}{(2.9)(5)(210)} = 0.102$$

Thus,

$$k_w = 1.27$$

And, using Eq. (7-10),

$$r_w = \frac{3}{52}(210) + 1.27 \cdot (\sqrt{3})(0.8) = 13.875, \text{ say 14 units}$$

7.5 Input Parameters for Simulation Models

The input parameters for the simulation study are given as follows:

/* Order amounts by different customers for different product types */

P1C1OrderAmount = 75, P1C2OrderAmount = 110, P1C3OrderAmount = 100, P2C4OrderAmount = 330;

/* Amount of components for batch processing */

BatchOfComp1 = 5, BatchOfComp2 = 5, BatchOfC1P2 = 5, BatchOfComp3 = 5;

/* Re-order points for different retailers */

ReOrderPointOfRE11P1 = 8, ReOrderPointOfRE12P1 = 10, ReOrderPointOfRE13P1 = 14;

/* Re-order points for warehouse, product type 1, and components */

ROPW1P1 = 32, ROPP1Inv = 26, ROPCM1Inv = 12, ROPCM2Inv = 8, ROPCM3Inv = 4;

/* Economic order quantities for retailers and warehouse */

EOQW1RE11 = 20, EOQW1RE12 = 25, EOQW1RE13 = 28, EOQP1W1 = 60;

/* Economic production quantity for product 1 and economic order quantities different components */

EPQP1Inv = 42, EOQCM1Inv = 20, EOQCM2Inv = 10, EOQCM3Inv = 10;

/* Starting values of product 1 inventory levels at retailers and warehouse */

SVRE11P1Inv = ReOrderPointOfRE11P1+EOQW1RE11,

SVRE12P1Inv = ReOrderPointOfRE12P1+EOQW1RE12,

SVRE13P1Inv = ReOrderPointOfRE13P1+EOQW1RE13,

SVW1P1Inv = ROPW1P1+EOQP1W1;

/* Starting values of inventory levels for different components */

SVCM1Inv = ROPCM1Inv+EOQCM1Inv,

SVCM2Inv = ROPCM2Inv+EOQCM2Inv,

SVCM3Inv = ROPCM3Inv+EOQCM3Inv);

/* Amount of products for batch transportation */

BatchOfP1C1Trans = 9; BatchOfP1C2Trans = 15; BatchOfP1C3Trans = 20;

/* Cost related variables */

WHOdrCost = 10$, / warehouse order price per unit of product /

REOdrCost =15$, / retailers' order price per unit of product /

RMREOdrCost = 7$, / order price per unit raw material /

WHUnitVarCost =1$, / unit value of the product at the warehouse /

REUnitVarCost = 5$, / unit value of the product at the retailers /

CarryingCost = 2 $/$/unit time, / inventory carrying cost /

BackOrderCost = 2.9 $/unit, / backorder cost /

HoldingCostWH = WHUnitVarCost*CarryingCost, / holding cost at warehouse /

HoldingCostRE = REUnitVarCost*CarryingCost, / holding cost at retailers /

M1SetupCost = 10$, / machine 1 set-up cost for each time /

M2SetupCost = 15$, / machine 2 set-up cost for each time /

M3SetupCost = 18$, / machine 3 set-up cost for each time /

7.6 Output Data Analysis for Terminating Simulation Models

Since all the simulations in this dissertation start at a defined state and end when they reach some other defined state, they are terminating simulation models. An initial state might be the number of components and finished products in the systems at the beginning of a workday. A terminating state might be when a particular number of products have been completed. Consider, for example, a supply chain that receives 100 orders to manufacture and distribute 500 products. We might be interested in knowing how long it will take to produce and send the 500 products. The simulation run starts with the specific number of products in inventory and is terminated when the 10^{th} order is filled (some orders might be backlogged). Since terminating simulation always contains transient periods that are part of the analysis, resource utilizations and fill-rates have the most meaning for successive time intervals during the simulation.

7.6.1 Experimenting with Terminating Simulations

Experiments are conducted by making several simulation runs of the period of interest using a different random seed for each run. This procedure enables statistically independent and unbiased observations to be on the response variables of interest in the system over the period simulated.

7.6.1.1 Selecting the Initial Model State

Since the initial conditions for a terminating simulation generally affect the desired measures of performance, these conditions should be representative of those for the actual system. For the simulation models in this research, some initial conditions such as safety stock levels, reorder point levels, and initial inventory levels for components and products are specified through the approximate inventory analysis in above section. The initial state of the model at the beginning of the simulation is that no orders are in the supply chain network and all resources (machines) are idle. The system is idle until orders begin to arrive in the system as described by the logic in the models.

7.6.1.2 Selecting a Terminating Event

A terminating event is an event that occurs during the simulation that causes the simulation run to end. In this research, the terminating event would be that all orders are filled and products are sent to customers. Notice that some orders might be backlogged.

7.6.1.3 Determining the Number of Replications

Experiments involving terminating simulations are usually conducted by making several simulation runs or replications of the period of interest using a different random number seed for each run. This procedure enables statistically independent and unbiased observations to be made on response variables of interest in the system.

The number of replications that will provide an adequate sample size for meeting the desired error amount *e* and significance level α can be approximately calculated as follows (Law and Kelton 1999):

$$n = \left[\frac{(Z_{a/2}) \cdot s}{e} \right]^2 \qquad (7\text{-}12)$$

The value of $Z_{a/2}$ can be found in a table for the standard normal distribution.

Note that before the equation can be used, an initial sample of observations must be collected to compute the sample standard deviation *s* of the output from the system.

Since there are three retailers and three commonality-index values in the simulation study, there will be a corresponding performance measure for each combination. We choose the sample standard deviation with the maximal value to compute the number of replications. The reason is that the higher standard deviation value will generate the larger number of replications.

From the initial sample of 50 observations of fill-rate performance of the simulation models with component commonality, *s* can be estimated as 0.11. The number of replications can be computed as follows:

Given: P = confidence level = 0.95,

α = significance level = 1-P = 1- 0.95 = 0.05,

e = 0.01,

$s = 0.11$

From the standard normal distribution table, we find $Z_{a/2} = Z_{0.025} = 1.96$.

$$n = \left[\frac{(1.96)\cdot(0.11)}{0.01}\right]^2 = 464.83 \text{ observations}$$

A fractional number of replications cannot be conducted, so the result is typically rounded up. Thus, $n \approx 465$ observations.

Similarly, from the initial sample of 50 observations of utilization-rate performance of the simulation models with component commonality, s can be estimated as 0.088. The amount of error between the estimated and the true mean (i.e., e) is specified as 0.01.

$$n = \left[\frac{(1.96)\cdot(0.088)}{0.01}\right]^2 = 297.5$$

Thus, $n \approx 298$ observations.

From the initial sample of 50 observations of delivery-time performance of the simulation models with component commonality, s can be estimated as 153. The amount of error between the estimated and the true mean (i.e., e) is specified as 15.

$$n = \left[\frac{(1.96)\cdot(153)}{15}\right]^2 = 399.68$$

Thus, $n \approx 400$ observations.

In general, the accuracy of the estimates improves as the number of replications increases. However, after a point, only modest improvements in accuracy are made through conducting additional replications of the experiment. Therefore, it is sometimes necessary to compromise on a desired level of replications of the model. In this research, the number of replications for all simulation models is chosen as 500.

7.7 Simulation Models and Statistical Analysis for Multi-Echelon Distribution Systems

Following the modeling framework for integrated supply chain networks presented in Chapter 5, we can build the simulation models for multi-echelon distribution systems with installation stock reorder point policy (see Figure 7.4).

Similarly, we can build the simulation model for a multi-echelon distribution system with echelon stock reorder point policy. The snapshots for the output of the simulation models are given in Figure 7.5.

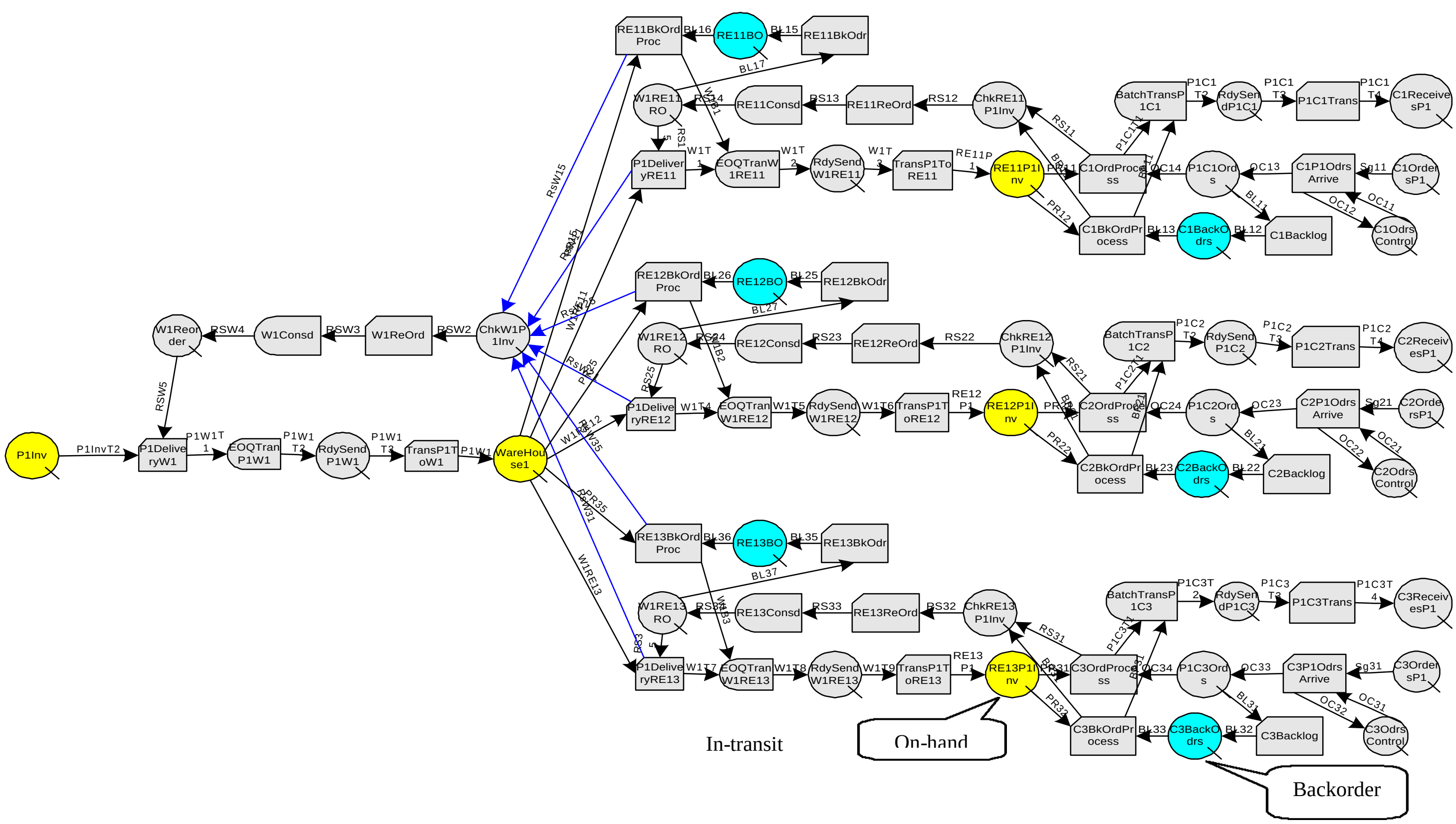

Figure 7.4 Simulation model for a multi-echelon distribution system with installation stock reorder point policy