CHAPTER 14

Simulation of Manufacturing Systems

Recommended sections for a first reading: 14.1, 14.2, 14.4, 14.5

14.1 INTRODUCTION

There continues to be widespread use of simulation to design and "optimize" manufacturing systems. As a matter of fact, it could arguably be said that simulation is more widely applied to manufacturing systems than to any other application area. Some reasons for this include the following:

- Increased competition in many industries has resulted in greater emphasis on automation to improve productivity and quality. Since automated systems are more complex, they typically can only be analyzed by simulation.
- The cost of equipment and facilities can be quite large. For example, a new semiconductor manufacturing plant can cost a billion dollars or even more.
- The cost of computing has decreased dramatically as a result of faster and cheaper PCs.
- Improvements in simulation software (e.g., graphical user interfaces) have reduced model-development time, thereby allowing for more timely manufacturing analyses.
- The availability of animation has resulted in greater understanding and use of simulation by manufacturing managers.

The remainder of this chapter is organized as follows. In Sec. 14.2 we discuss the types of manufacturing issues typically addressed by simulation. Section 14.3 gives brief descriptions of FlexSim and ProModel, which are popular manufacturing-oriented simulation packages. A simulation model of the small factory considered in Chap. 3 is also given for each package. Modeling of manufacturing-system randomness, including machine downtimes, is discussed in Sec. 14.4. Sections 14.5 and 14.6 show in considerable detail how simulation is actually used to design and analyze a manufacturing system.

A good reference on manufacturing systems in general is Hopp and Spearman (2011). Many actual applications of simulation in manufacturing can be found in the *Proceedings of the Winter Simulation Conference*, which is published every December (see www.wintersim.org).

14.2 OBJECTIVES OF SIMULATION IN MANUFACTURING

Perhaps the greatest overall benefit of using simulation in a manufacturing environment is that it allows a manager or an engineer to obtain a *systemwide view* of the effect of "local" changes to the manufacturing system. If a change is made at a particular workstation, its impact on the performance of *this* station may be predictable. On the other hand, it may be difficult, if not impossible, to determine ahead of time the impact of this change on the performance of the *overall system.*

EXAMPLE 14.1. Suppose that a workstation with one machine has insufficient processing capacity to handle its workload (i.e., its processing rate is less than the arrival rate of parts). Suppose further that it has been determined that adding a second machine will alleviate the capacity shortage at this station. However, this additional machine will also increase the throughput of parts from this station. This increased throughput will, in turn, show up as increased arrival rates to downstream workstations, which may cause new capacity shortages to occur, etc.

In addition to the above general benefit of simulation, there are a number of specific potential benefits from using simulation for manufacturing analyses, including:

- Increased throughput (parts produced per unit of time)
- Decreased times in system of parts
- Reduced in-process inventories of parts
- Increased utilizations of machines or workers
- Increased on-time deliveries of products to customers
- Reduced capital requirements (land, buildings, machines, etc.) or operating expenses
- Insurance that a proposed system design will, in fact, operate as expected
- Information gathered to build the simulation model will promote a greater understanding of the system, which often produces other benefits.
- A simulation model for a proposed system often causes system designers to think about certain significant issues (e.g., system control logic) long before they normally would.

EXAMPLE 14.2. The information gathered for a simulation model of a food-packing plant showed that the control logic for the conveyor system was not implemented correctly.

Simulation has successfully addressed a number of particular manufacturing issues, which we might classify into three general categories:

The need for and the quantity of equipment and personnel

- Number, type, and layout of machines for a particular objective (e.g., production of 1000 parts per week)
- Requirements for material-handling systems and other support equipment (e.g., pallets and fixtures)
- Location and size of inventory buffers
- Evaluation of a change in product volume or mix (e.g., impact of new products)
- Evaluation of the effect of a new piece of equipment (e.g., a robot) on an existing manufacturing line
- Evaluation of capital investments
- Labor-requirements planning
- Number of shifts

Performance evaluation

- Throughput analysis
- Time-in-system analysis
- Bottleneck analysis [i.e., determining the location of the constraining resource(s)]

Evaluation of operational procedures

- Production scheduling (i.e., evaluating proposed policies for dispatching orders to the shop floor, choosing batch sizes, loading parts at a workstation, and sequencing of parts through the workstations in the system)
- Policies for component-part or raw-material inventory levels
- Control strategies [e.g., for a conveyor system or an automated guided vehicle system (AGVS)]
- Reliability analysis (e.g., effect of preventive maintenance)
- Quality-control policies (e.g., Six Sigma)
- Just-in-time (JIT) strategies

There are several common measures of performance obtained from a simulation study of a manufacturing system, including:

- Throughput
- Time in system for parts (cycle time)
- Times parts spend in queues
- Times parts spend waiting for transport
- Times parts spend in transport
- Timeliness of deliveries (e.g., proportion of late orders)
- Sizes of in-process inventories (work-in-process or queue sizes)
- Utilization of equipment and personnel (i.e., proportion of time busy)
- Proportions of time that a machine is broken, starved (waiting for parts from a previous workstation), blocked (waiting for a finished part to be removed), or undergoing preventive maintenance
- Proportions of parts that are reworked or scrapped

14.3 SIMULATION SOFTWARE FOR MANUFACTURING APPLICATIONS

The simulation-software requirements for manufacturing applications are not fundamentally different from those for other simulation applications, with one exception. Most modern manufacturing facilities contain material-handling systems, which are often difficult to model correctly. Therefore, in addition to the software features discussed in Chap. 3, it is desirable for simulation packages used in manufacturing to have flexible, easy-to-use material-handling modules. Important classes of material-handling systems are *forklift trucks*, AGVS with contention for guide paths, *transport conveyors* (equal distance between parts), *accumulating* (or queueing) *conveyors*, *power-and-free conveyors*, *automated storage-and-retrieval systems* (AS/RS), *bridge cranes*, and *robots*. Note that just because a particular software package contains conveyor constructs doesn't necessarily mean that they are appropriate for a given application. Indeed, real-world conveyor systems come in a wide variety of forms, and different software packages have varying degrees of conveyor capabilities.

In Chap. 3 we defined general-purpose and application-oriented simulation packages, and then we discussed three general-purpose packages in some detail. General-purpose packages usually offer considerable modeling flexibility and are widely used to simulate manufacturing systems. Furthermore, some of these products (e.g., Arena and ExtendSim) provide modeling constructs (e.g., conveyors) specifically for manufacturing. There are also many simulation packages designed specifically for use in a manufacturing environment. In Secs. 14.3.1 and 14.3.2 we give descriptions of FlexSim and ProModel, respectively, which are, at the time of this writing, two popular manufacturing-oriented simulation packages. In each case, we also show how to build a model of the small factory considered in Sec. 3.5. Section 14.3.3 lists some additional manufacturing-oriented simulation packages.

14.3.1 FlexSim

FlexSim [see Beaverstock et al. (2013) and FlexSim (2013)] is a true object-oriented simulation package for manufacturing, material handling, warehousing, and flow processes marketed by FlexSim Software Products (Orem, Utah). A model is constructed by dragging and dropping "objects" into the "Model View" and then editing their parameters using dialog boxes. FlexSim can model a wide variety of manufacturing configurations, since existing objects can be fully customized to meet specific requirements. These customized objects can then be placed in the library for reuse in current or future modeling applications. A model can also have an unlimited number of levels of hierarchy and use all aspects of object-oriented technology (i.e., encapsulation, inheritance, and polymorphism, as discussed in Sec. 3.6).

FlexSim provides three-dimensional, prospective-projection model building and animation by default; however, the user has the option to switch to an orthographic view or display both views simultaneously.

Material-handling devices available in FlexSim include conveyors (transport and accumulating), forklift trucks, AGVS, AS/RS, cranes, elevators, robots, and operators. FlexSim provides preempting and priority processing for capturing details of product movement and processing.

The FlexSim software includes a cost model that allows one to account for the profit for each part produced and also for the costs associated with machines, labor, work-in-process, etc.

There are an unlimited number of random-number streams available in FlexSim. Furthermore, the user has access to 24 standard theoretical probability distributions and also to empirical distributions. The time to failure of a machine can be based on busy time, calendar time, or a user-defined event.

There is an "Experimenter" that can be used to automatically make independent replications for each of a number of different scenarios, and to obtain point estimates and confidence intervals for performance measures of interest. Furthermore, the replications can be simultaneously executed across multiple processor cores. A number of plots are available, including time plots, histograms, bar charts, pie charts, and Gantt charts.

The ExpertFit distribution-fitting software (see Sec. 6.7) is bundled with FlexSim, while the OptQuest "optimization" module (see Sec. 12.5.2) is available as an option. FlexSim Software Products also develops and markets the FlexSim Healthcare simulation package.

The FlexSim model of the manufacturing system consists of the six objects shown in Fig. 14.1, which is the orthographic view of the model. The dialog box

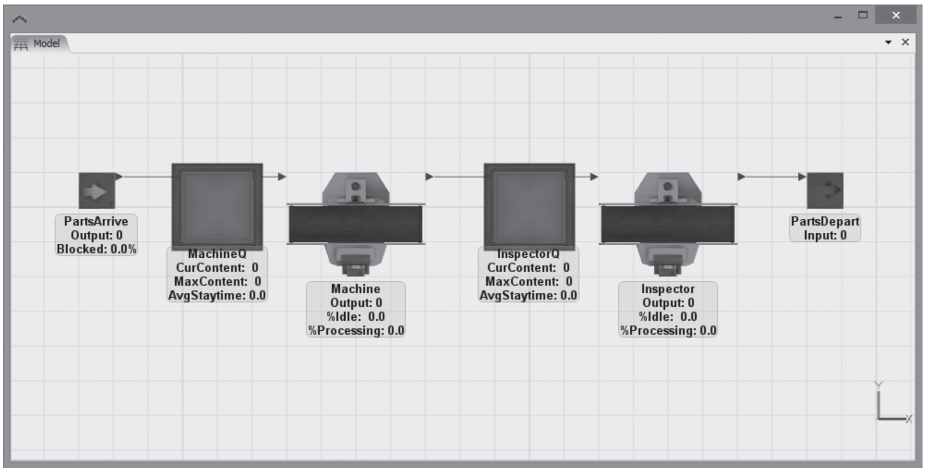
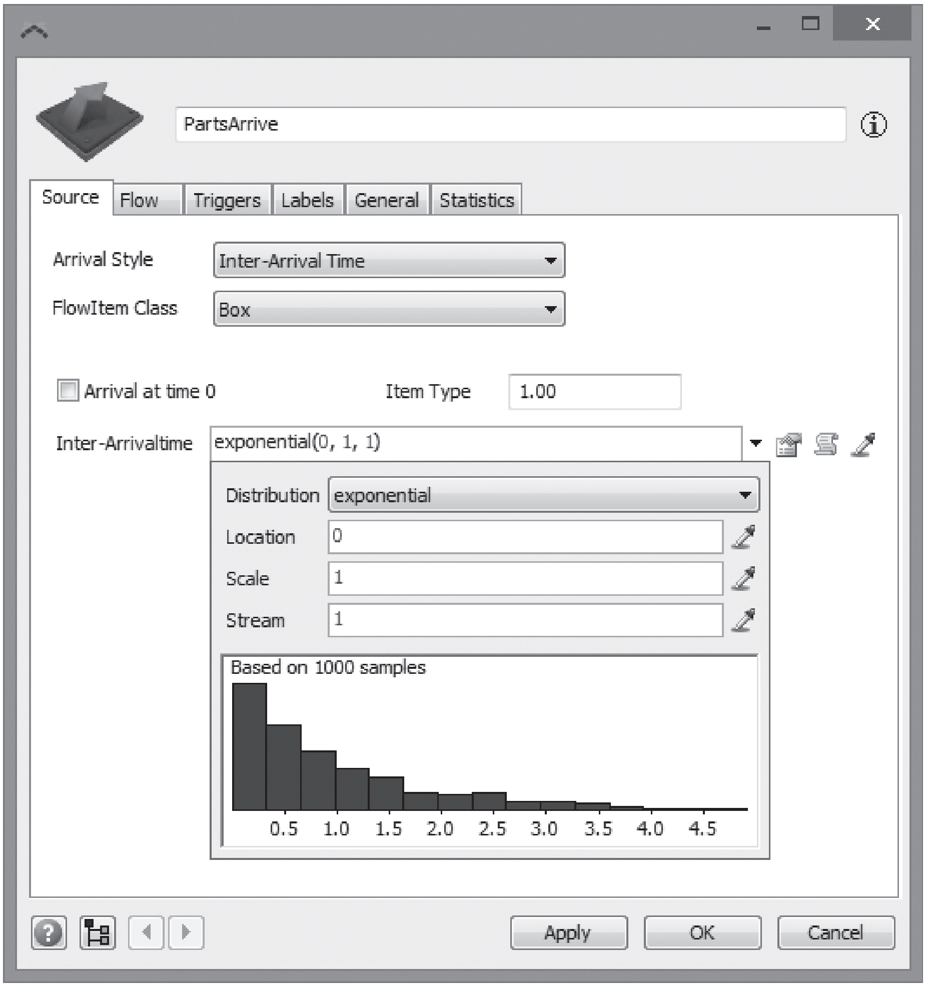


FIGURE 14.1
FlexSim model for the manufacturing system, as shown in the orthographic view.


PartsArrive

Arrival Style: Inter-Arrival Time

FlowItem Class: Box

Arrival at time 0 ☐ Item Type: 1.00

Inter-Arrivaltime: exponential(0, 1, 1)

Distribution: exponential

Location: 0

Scale: 1

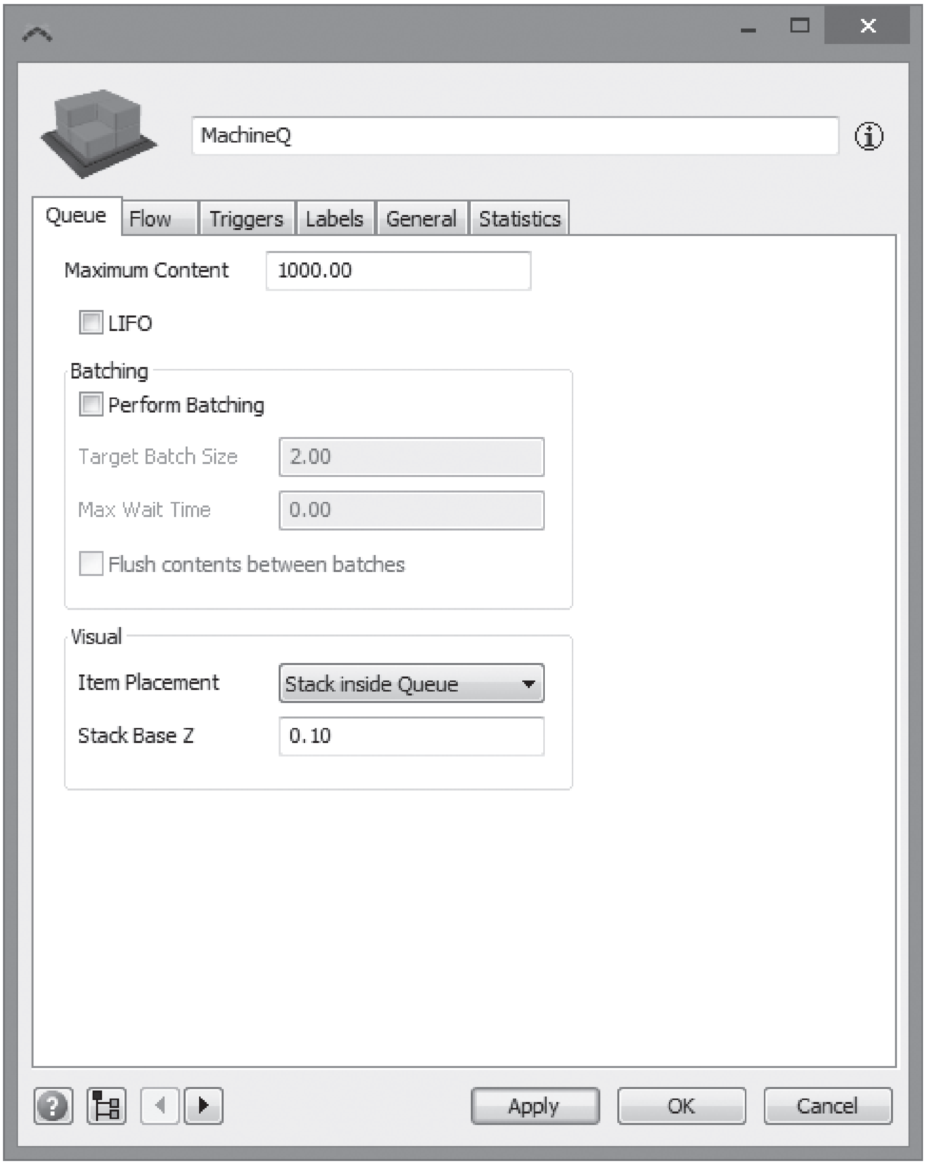
Stream: 1

Based on 1000 samples

FIGURE 14.2
Dialog box for the FlexSim Source object "PartsArrive."

for the "Source" object named "PartsArrive" (the left-most object in Figure 14.1) is shown in Fig. 14.2; here we specify that the interarrival times of parts (called "flowitems" in FlexSim) are exponentially distributed with a mean of 1 (and a location parameter of 0) and use random-number stream 1 (see Chap. 7). (The time unit for the simulation model is set to minutes at the beginning of the model-building process.) The statistical-distribution dialog box displays a histogram of 1000 generated interarrival times.

The next object is a "Queue" object named "MachineQ," whose dialog box is shown in Fig. 14.3. The dialog box for the "Processor" object named "Machine" is



MachineQ

Maximum Content 1000.00

☐ LIFO

Batching

☐ Perform Batching

Target Batch Size 2.00

Max Wait Time 0.00

☐ Flush contents between batches

Visual

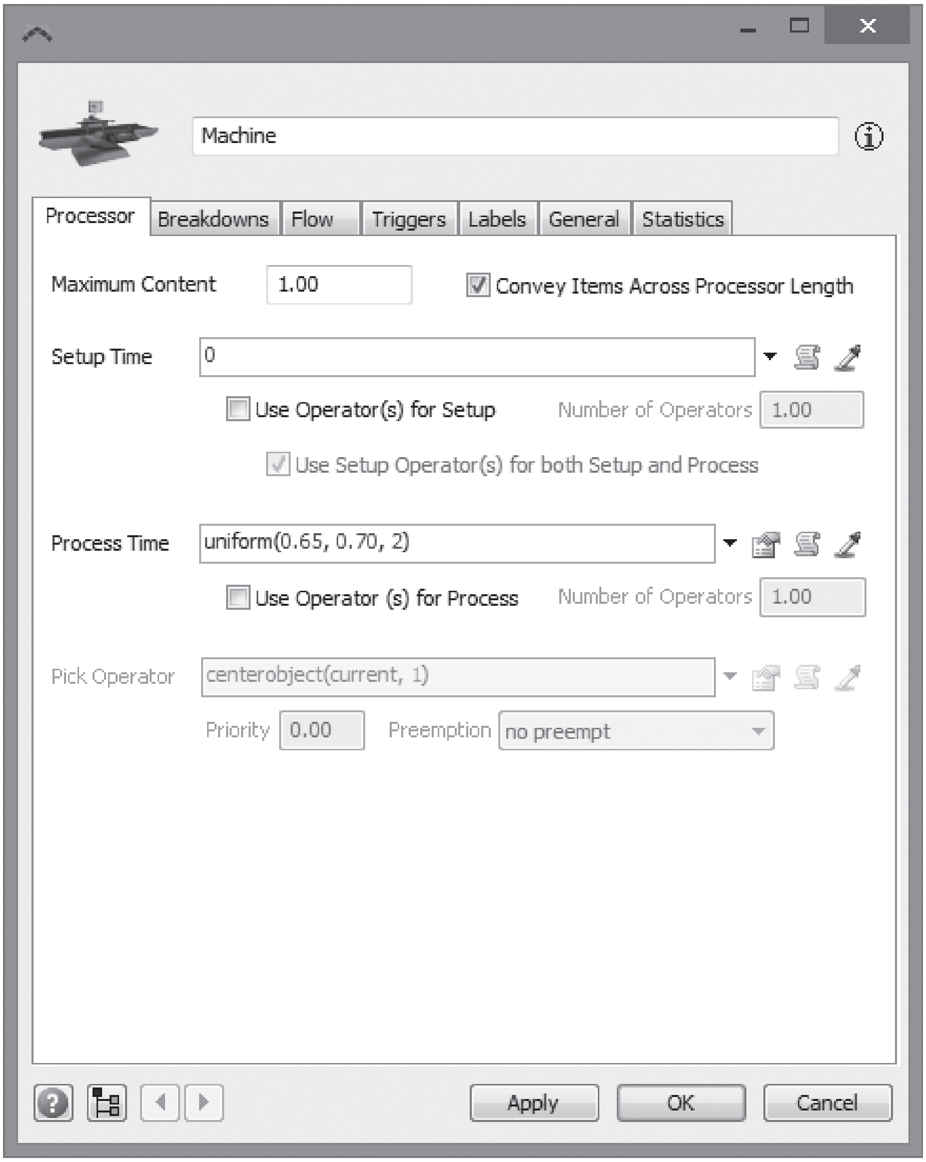
Item Placement Stack inside Queue

Stack Base Z 0.10

FIGURE 14.3
Dialog box for the FlexSim Queue object “MachineQ.”

shown in Fig. 14.4, where we specify that processing times are uniformly distributed with a minimum value of 0.65 and a maximum value of 0.70, and we use random-number stream 2.

The dialog box for the Queue object named “InspectorQ” is similar to that for the MachineQ object and is not shown. The dialog box for the Processor


Machine

Processor | Breakdowns | Flow | Triggers | Labels | General | Statistics

Maximum Content 1.00 ☑ Convey Items Across Processor Length

Setup Time 0

☐ Use Operator(s) for Setup Number of Operators 1.00

☑ Use Setup Operator(s) for both Setup and Process

Process Time uniform(0.65, 0.70, 2)

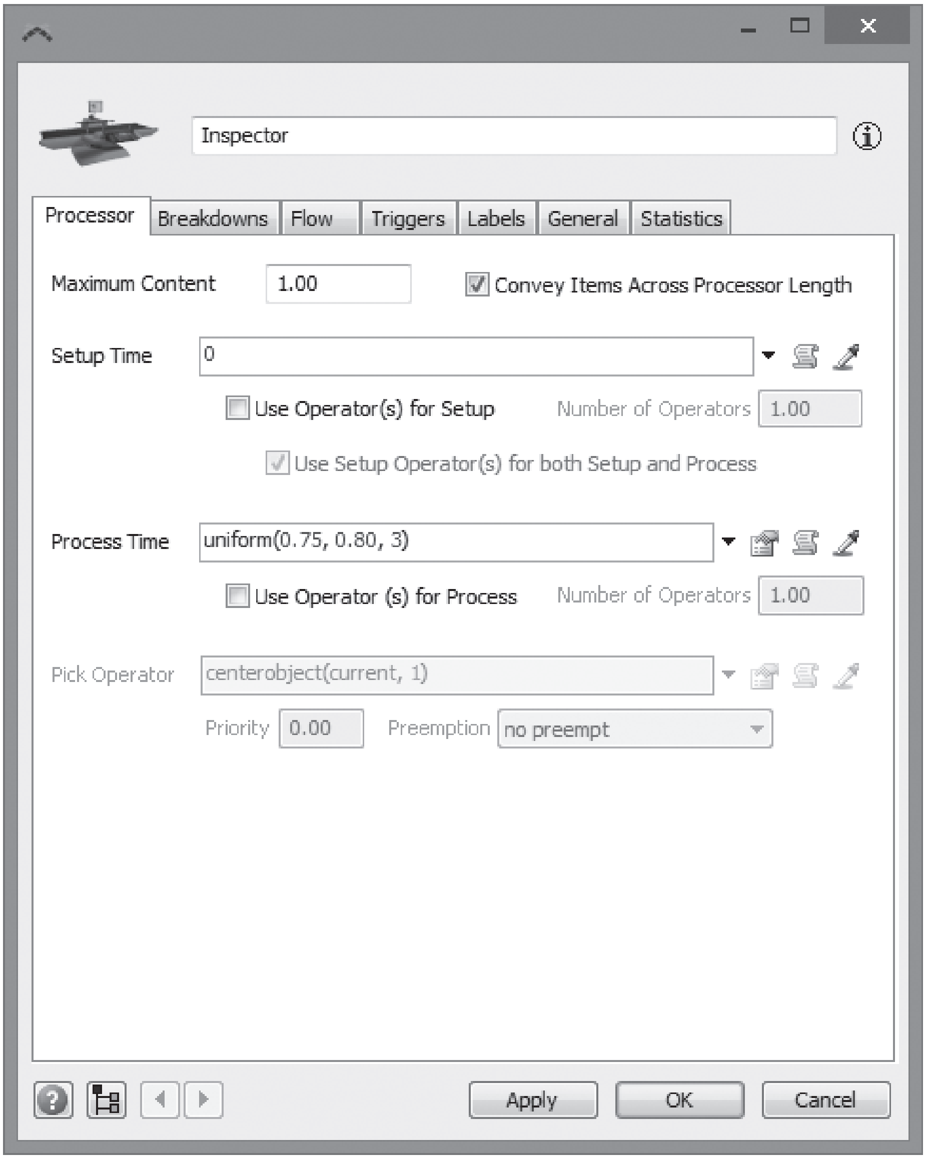
☐ Use Operator (s) for Process Number of Operators 1.00

Pick Operator centerobject(current, 1)

Priority 0.00 Preemption no preempt

FIGURE 14.4
Dialog box for the FlexSim Processor object "Machine."

object named "Inspector," which is similar to that for the Machine object, is shown in Fig. 14.5. Here we specify that inspection times are uniformly distributed with a minimum value of 0.75 and a maximum value of 0.80, and we use random-number stream 3. Also, if we click on the "Flow" tab near the top of the screen, we can access the dialog box shown in Fig. 14.6. Here we specify that


Inspector

Maximum Content 1.00

[✓] Convey Items Across Processor Length

Setup Time 0

[ ] Use Operator(s) for Setup — Number of Operators 1.00

[✓] Use Setup Operator(s) for both Setup and Process

Process Time uniform(0.75, 0.80, 3)

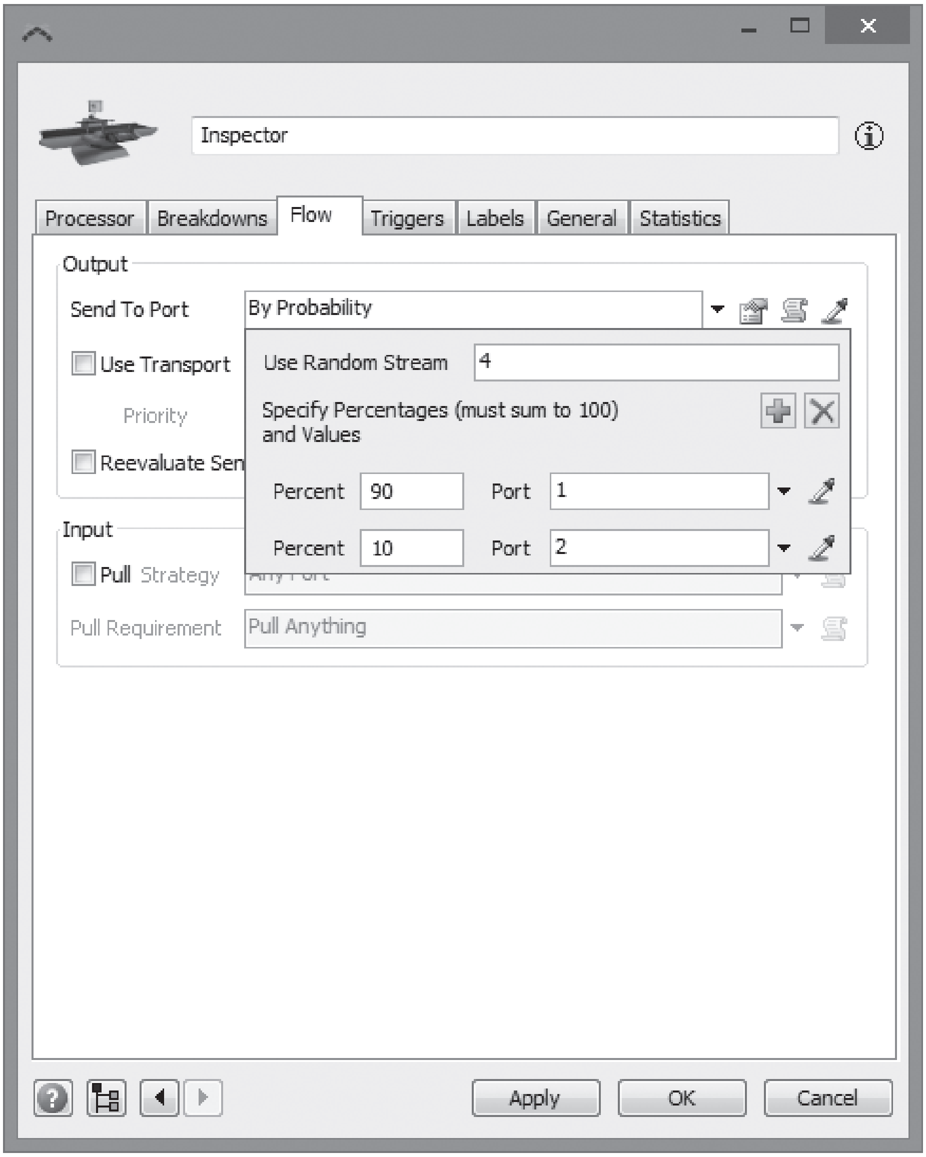
[ ] Use Operator (s) for Process — Number of Operators 1.00

Pick Operator centerobject(current, 1)

Priority 0.00 — Preemption no preempt

FIGURE 14.5
Dialog box for the FlexSim Processor object "Inspector."

90 percent of the flowitems (i.e., those that are good) go to output port 1 (using random-number stream 4), which is connected to the "Sink" object named "PartsDepart" (its dialog box is not shown). The remaining 10 percent of the parts (i.e., those that are bad) go to output port 2, where they are sent back to the MachineQ object to be reworked. The simulation run length is specified to be


Inspector

Processor | Breakdowns | Flow | Triggers | Labels | General | Statistics

Output

Send To Port: By Probability

Use Transport

Priority

Reevaluate Sen

Use Random Stream: 4

Specify Percentages (must sum to 100) and Values

Percent: 90 Port: 1

Percent: 10 Port: 2

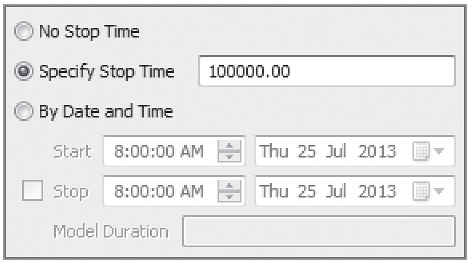
Input

Pull Strategy

Pull Requirement: Pull Anything

FIGURE 14.6
FlexSim dialog box for specifying the routing of parts from "Inspector."

100,000 time units by using a dialog box (see Fig. 14.7) that is accessed from the "Run Time" pull-down menu at the top of the screen. The results from running the simulation model are shown in Table 14.1, and a perspective-projection view is given in Fig. 14.8.


No Stop Time

Specify Stop Time [✓] 100000.00

By Date and Time

Start 8:00:00 AM Thu 25 Jul 2013

Stop 8:00:00 AM Thu 25 Jul 2013

Model Duration

FIGURE 14.7
FlexSim dialog box for specifying the simulation run length.

14.3.2 ProModel

ProModel [see Harrell et al. (2012) and ProModel (2013)] is a manufacturing-oriented simulation package developed and marketed by ProModel Corporation (Orem, Utah). The following are some of the basic modeling constructs, the first four of which must be in every model:

Locations	Used to model machines, queues, conveyors, or tanks (see below)
Entities	Used to represent parts, raw materials, or information
Arrivals	Used to specify how parts enter the system
Processes	Used to define the routing of parts through the system and to specify what operations are performed for each part at each location
Resources	Used to model static or dynamic resources such as workers or forklift trucks

A model can be constructed graphically (e.g., routings for parts can be defined by clicking on graphical locations), by filling in data fields, and by "programming" with an internal pseudo-language. It is also possible to call external subroutines written in, say, C or C++. Customized front- and back-end interfaces can be developed using ProModel's ActiveX capability. For example, an Excel interface can easily be set up for creating or modifying models. ProModel provides two-dimensional animation, which is created automatically when the model is developed. Three-dimensional animation is available using ProModel's 3D Animator.

TABLE 14.1
Simulation results for the FlexSim model of the manufacturing system

Output statistic	Observed value
Average time in system	4.42
Machine utilization	0.75
Inspector utilization	0.86
Average delay in machine queue	1.01
Average number in machine queue	1.12
Average delay in inspector queue	1.52
Average number in inspector queue	1.68

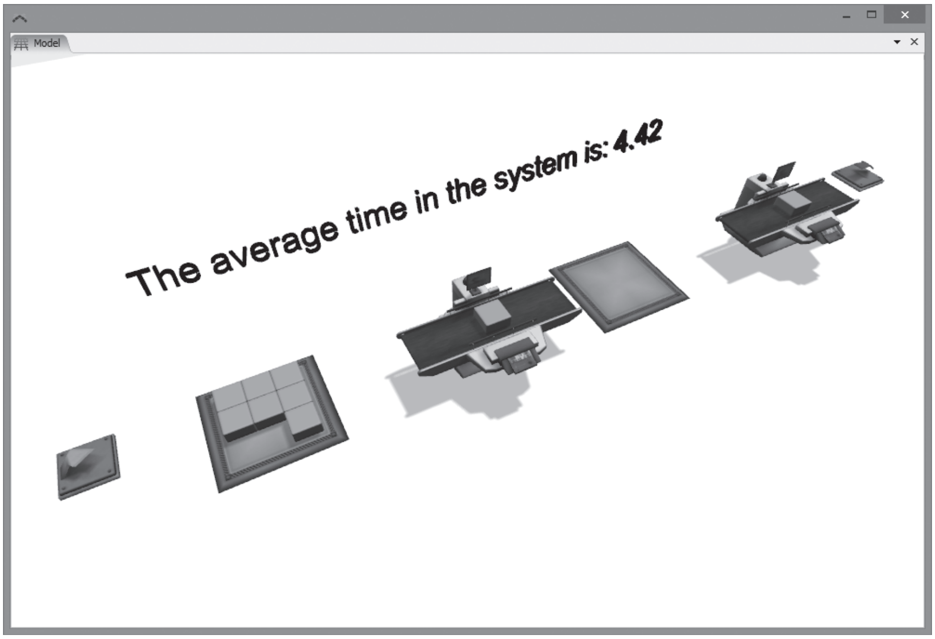


FIGURE 14.8
FlexSim model for the manufacturing system, as shown in perspective-projection view.

Material-handling capabilities in ProModel include manual handling, transport conveyors, accumulating conveyors, forklift trucks, AGVS, and bridge cranes. ProModel also has a tank construct for modeling continuous-flow systems. ProModel includes a costing feature that allows one to assign costs to locations, resources, and entities that are then tracked over time.

There are 100 different random-number streams available in ProModel. Furthermore, the user has access to 15 standard theoretical probability distributions and also to empirical distributions. The time to failure of a machine may be based on busy time, calendar time, the number of completed parts, or a signal from another part of the model.

There is a “Scenario Manager” that can be used to automatically make independent replications for each of a number of different scenarios. The results from the simulation runs are displayed in ProModel’s “Output Viewer” in the form of tables and graphs, including state graphs (e.g., whether a machine is busy, idle, down, etc.), time plots, histograms, and pie charts. Point estimates and confidence intervals for performance measures of interest can also be displayed. Custom reports can be created that display a specific set of tables and graphs.

In addition to providing the ability to export data to Excel, ProModel also links and integrates with Minitab to provide users with a Six Sigma analysis capability. For each scenario of interest, two charts are automatically generated in Minitab for each Six Sigma metric, namely, the Capability Analysis Chart and the Capability Sixpack Chart. The SimRunner optimization module is also included with ProModel. ProModel Corporation also develops and markets the MedModel, ServiceModel, and ProcessSimulator (a Microsoft Visio add-in) simulation packages.

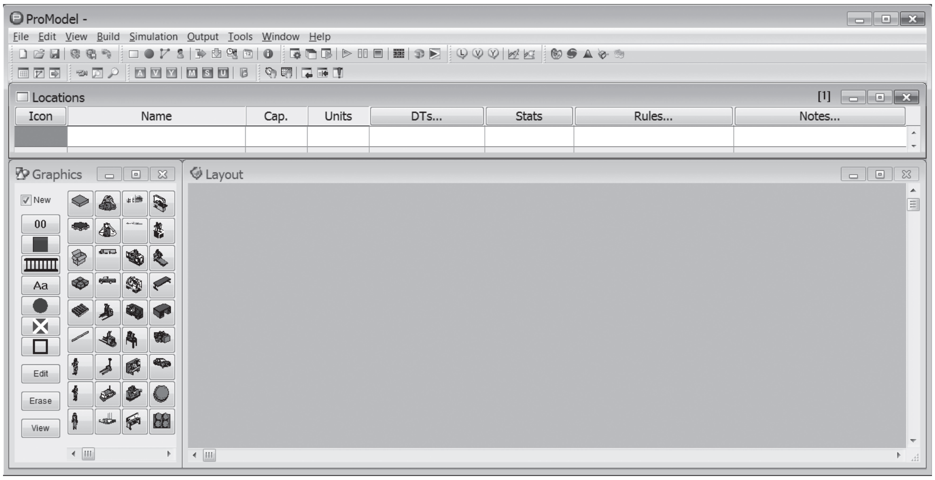
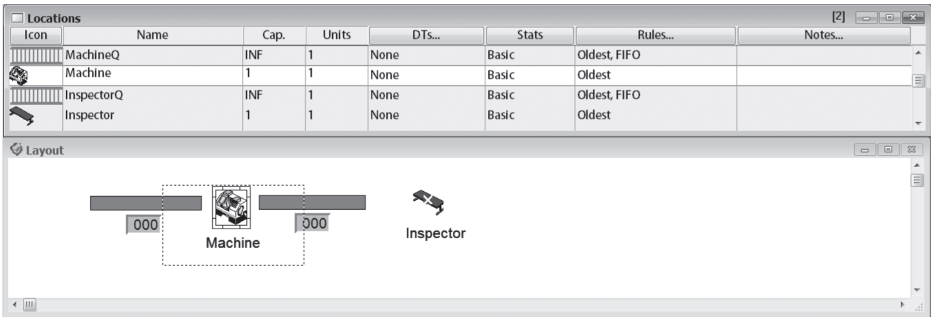


FIGURE 14.9
Locations Module for ProModel.

The ProModel model for the manufacturing system uses “Locations,” “Entities,” “Arrivals,” and “Processes” modeling constructs. Locations, which will be used to represent the machine, the inspector, and their queues, are selected from the “Build” drop-down menu, or by selecting the Locations icon on the toolbar. The resulting “Locations Module,” which consists of three windows, is shown in Fig. 14.9. The “Locations Graphics” window is shown in the lower-left portion of the screen, the “Locations Edit” table across the top of the screen, and the “Layout” window in the lower-right portion of the screen. For each desired model location, a location icon is selected from the Locations Graphics window and placed in the Layout window. A new record corresponding to this location is automatically added to the Locations Edit table, whose fields (Name, Capacity, etc.) can then be edited in an appropriate way. The Locations Edit table and Layout window for the manufacturing system are shown in Fig. 14.10. In particular, the fields for the “Machine” record in the Edit table are as follows:

Cap.	The capacity of the Machine location (i.e., the number of parallel machines) is 1.
Units	The number of separate units of this location (each having the same characteristics) is 1.
DTs	There are no downtimes for this location.
Stats	Only “Basic” statistics (i.e., machine utilization and average processing time) will be computed for this location.
Rules	The Machine, when available, will pick that part in the queue that has been waiting the longest (i.e., the “Oldest”).

The horizontal rectangles in the Layout window represent the machine and the inspector queues. Below each queue is a counter, which displays the current number of parts in the queue as the model is running.

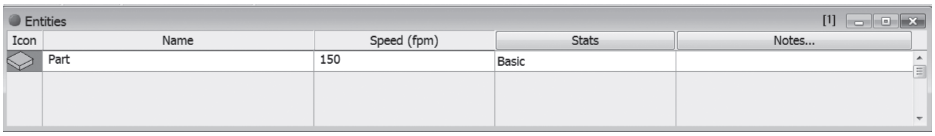

Locations

Icon	Name	Cap.	Units	DTs...	Stats	Rules...	Notes...
	MachineQ	INF	1	None	Basic	Oldest, FIFO	
	Machine	1	1	None	Basic	Oldest	
	InspectorQ	INF	1	None	Basic	Oldest, FIFO	
	Inspector	1	1	None	Basic	Oldest	

FIGURE 14.10
Locations Edit table and Layout window for the ProModel model.

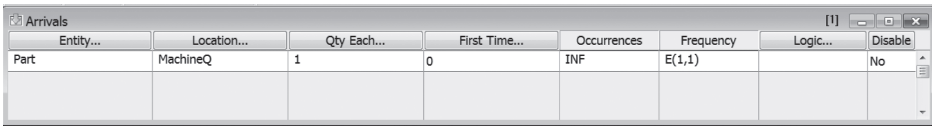
Entities, which are used to represent parts in this model, are selected from the Build menu, or by selecting the Entities icon on the toolbar. This results in the display of the "Entities Module," which consists of an "Entities Graphics" window, an "Entities Edit" table, and the Layout window. An entity is specified graphically by selecting an icon from the Entities Graphics window and then editing the record that automatically appears in the Entities Edit table. The Entities Edit table for this model is shown in Fig. 14.11. The "Speed" of an entity is not relevant for this model.

Arrivals, which are used to specify how entities arrive to the system, are also selected from the Build menu or from the toolbar. This results in the display of the "Arrivals Module," which consists of an "Arrivals Tools" window, an "Arrivals Edit" table, and the Layout window. To specify the manner in which an entity arrives, select the desired entity ("Part" for this model) from those listed in the Arrivals Tools window, and click in the Layout window on the location at which entities are to arrive ("MachineQ" for our model). The Arrivals Edit table for the model is shown in Fig. 14.12. The "E(1,1)" in the "Frequency" field specifies that parts have exponentially distributed (denoted "E") interarrival times with a mean of 1 minute (the default time unit), and that random-number stream 1 is being used (see Chap. 7).


Entities

Icon	Name	Speed (fpm)	Stats	Notes...
	Part	150	Basic	

FIGURE 14.11
Entities Edit table for the ProModel model.


Arrivals

Entity...	Location...	Qty Each...	First Time...	Occurrences	Frequency	Logic...	Disable
Part	MachineQ	1	0	INF	E(1,1)		No

FIGURE 14.12
Arrivals Edit table for the ProModel model.

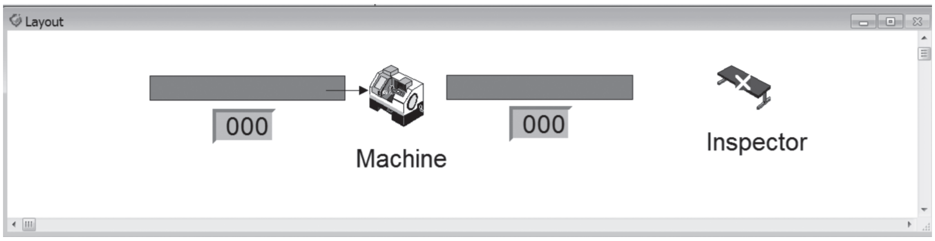


FIGURE 14.13
Layout window showing the route from “MachineQ” to “Machine” for the ProModel model.

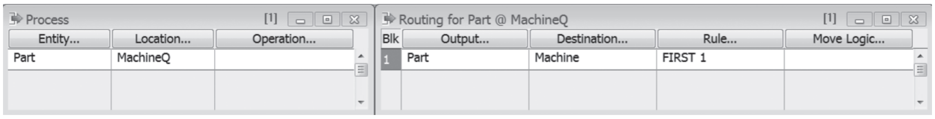
The “Logic” field could be used to execute certain logic at the instant that each entity arrives (e.g., assigning attribute values to the entity).

Selecting “Processing” from the Build menu (or selecting its icon on the toolbar) displays the “Processing Module,” which consists of the “Process Edit” table, the “Routing Edit” table, the “Process Tools” window, and the Layout window. To specify the routing (processing) of an entity graphically, complete the following steps:

1. Select an entity (Part for our model) from the entity list in the Process Tools window. The record for the location at which the entity arrives (MachineQ for our model) is highlighted in the Process Edit table.
2. Click on this location in the Layout window and a rubber-banding routing line appears starting at this location.
3. Click on the destination (succeeding) location for the entity (Machine for our model).

The Layout window for the simulation model after the routing from MachineQ to Machine has been specified is shown in Fig. 14.13. The corresponding Process Edit table and Routing Edit table are shown in Fig. 14.14. For our model, Part is both the entity arriving to and departing from the MachineQ location. (In a more complicated model, a raw-material entity could arrive to a machine and a completed-part entity could depart from the machine.) After the modeling for MachineQ is completed, the routing from Machine to “InspectorQ” is specified in a similar manner. For the Machine record in the Process Edit table (see Fig. 14.15), we must specify that processing times (see the “Operation” field) are uniformly distributed on the interval [0.65, 0.70] minute, which is denoted by “WAIT U(0.675, 0.025, 2).” (The random-number stream is 2.) The routing from InspectorQ to “Inspector” is then specified in a similar manner.

Finally, we must specify the routing out of the Inspector location, which is a little bit more complicated. The Process Edit table and Routing Edit table for this step are shown in Fig. 14.15. There are two routes out of Inspector. Either parts

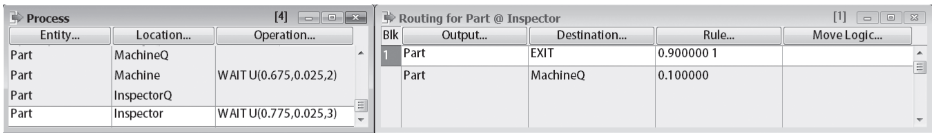

Process [1]

Entity...	Location...	Operation...
Part	MachineQ	

Routing for Part @ MachineQ [1]

Blk	Output...	Destination...	Rule...	Move Logic...
1	Part	Machine	FIRST 1	

FIGURE 14.14
Process Edit table and Routing Edit table with the “MachineQ record” selected for the ProModel model.



Process [4]

Entity...	Location...	Operation...
Part	MachineQ	
Part	Machine	WAIT U(0.675,0.025,2)
Part	InspectorQ	
Part	Inspector	WAIT U(0.775,0.025,3)

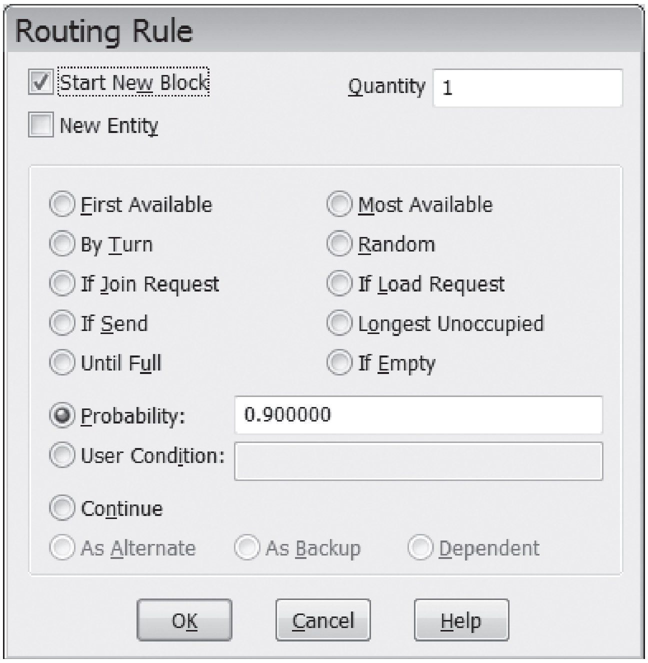
Routing for Part @ Inspector [1]

Blk	Output...	Destination...	Rule...	Move Logic...
1	Part	EXIT	0.900000 1	
	Part	MachineQ	0.100000	

FIGURE 14.15
Process Edit table and Routing Edit table with the "Inspector record" selected for the ProModel model.

leave the system by specifying "EXIT" as the "Destination" with a probability of 0.9, or parts go back to MachineQ with a probability of 0.1. This probabilistic routing is defined by double-clicking on the "Rule" field for each of the routings, selecting "Probability" in the resulting "Routing Rule" dialog box, and then entering the appropriate probability value (see Fig. 14.16). (Note we have also specified that inspection times are uniformly distributed on the interval [0.75, 0.80] minute and use stream 3.)

We specify that the simulation run length is 100,000 minutes by using the "Options" option (see Fig. 14.17) in the "Simulation" drop-down menu. After the simulation has been run, we can look at the results in the Output Viewer. The "Entity Summary" table (Fig. 14.18) shows that the average time in system for the entities called Part is 4.47 minutes.



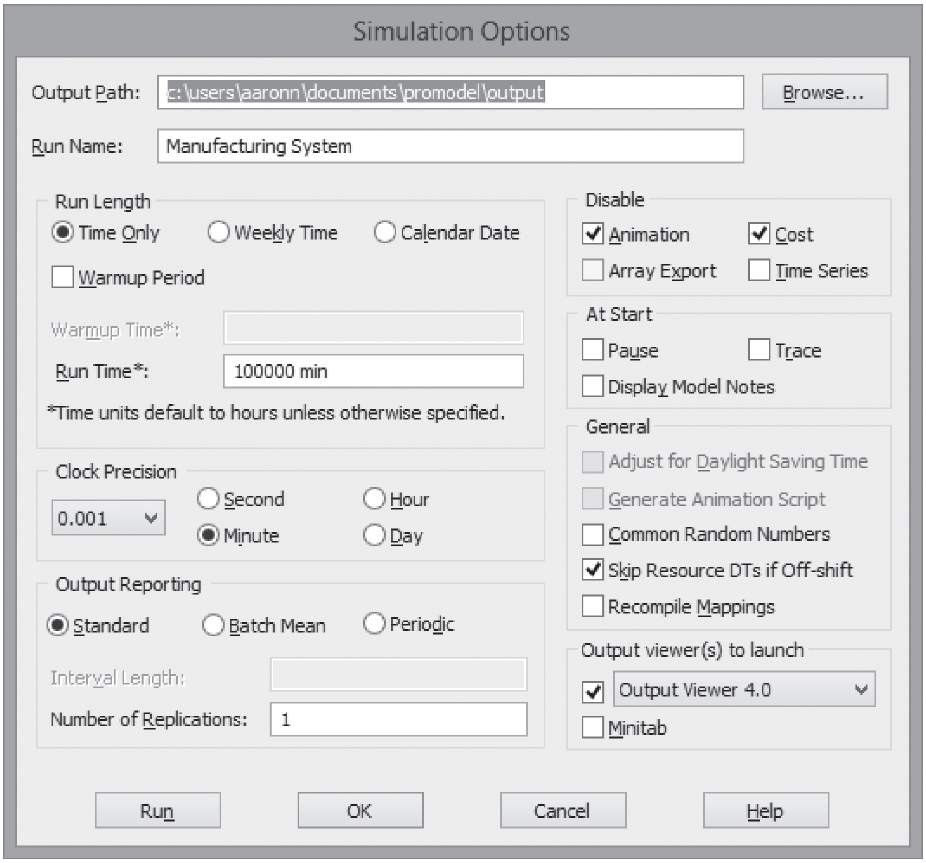
Routing Rule

[✓] Start New Block — Quantity: 1

[ ] New Entity

Probability: 0.900000 (selected)

FIGURE 14.16
Routing Rule dialog box for the ProModel model.


Simulation Options

Output Path: c:\users\aaronn\documents\promodel\output

Run Name: Manufacturing System

Run Length: [✓ Time Only] Weekly Time Calendar Date

☐ Warmup Period

Warmup Time*:

Run Time*: 100000 min

*Time units default to hours unless otherwise specified.

Clock Precision: 0.001 — Second [✓ Minute] Hour Day

Output Reporting: [✓ Standard] Batch Mean Periodic

Interval Length:

Number of Replications: 1

Disable: ✓ Animation ✓ Cost ☐ Array Export ☐ Time Series

At Start: ☐ Pause ☐ Trace ☐ Display Model Notes

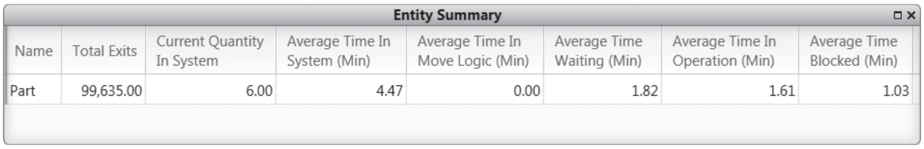
General: ☐ Adjust for Daylight Saving Time ☐ Generate Animation Script ☐ Common Random Numbers ✓ Skip Resource DTs if Off-shift ☐ Recompile Mappings

Output viewer(s) to launch: ✓ Output Viewer 4.0 ☐ Minitab

FIGURE 14.17
Simulation Options dialog box for the ProModel model.

14.3.3 Other Manufacturing-Oriented Simulation Packages

There are a number of other well-known, manufacturing-oriented simulation packages, including AutoMod [Banks (2004) and Applied (2013)], Enterprise Dynamics [INCONTROL (2013)], Plant Simulation [Siemens (2013)], and WITNESS [Lanner (2013)].


Entity Summary

Name	Total Exits	Current Quantity In System	Average Time In System (Min)	Average Time In Move Logic (Min)	Average Time Waiting (Min)	Average Time In Operation (Min)	Average Time Blocked (Min)
Part	99,635.00	6.00	4.47	0.00	1.82	1.61	1.03

FIGURE 14.18
Entity Summary table for the ProModel model of the manufacturing system.

14.4 MODELING SYSTEM RANDOMNESS

In Chap. 6 we presented a general discussion of how to choose input probability distributions for simulation models, and those ideas are still relevant here. We now discuss some additional topics related to modeling system randomness that are particularly germane to manufacturing systems, with our major emphasis being the representation of machine downtimes.

14.4.1 Sources of Randomness

We begin with a discussion of common sources of randomness in manufacturing systems. In particular, the following are possible examples of continuous distributions in manufacturing:

- Interarrival times of orders, parts, or raw materials
- Processing, assembly, or inspection times
- Times to failure of a machine (see Sec. 14.4.2)
- Times to repair a machine
- Loading and unloading times
- Setup times to change a machine over from one part type to another
- Rework
- Product yields

Note that in some cases the above quantities might be constant. For example, processing times for an automated machine might not vary appreciably. Also, automobile engines might arrive to a final assembly area with constant interarrival times of 1 minute.

There are actually two other common ways in which parts "enter" a manufacturing system. In some systems (e.g., a subassembly manufacturing line), it is often assumed that there is an unlimited supply of raw parts or materials in front of the line's first machine. Thus, the rate at which parts enter the system is the effective processing rate of the first machine, i.e., accounting for downtimes, blockage, etc. Jobs or orders may also arrive to a system in accordance with a production schedule, which specifies the time of arrival, the part type, and the order size for each order. In a simulation model, the production schedule might be read from an external file.

Histograms of observed processing (or assembly) times, times to failure, and repair times each tend to have a distinctive shape, and examples of these three types of data are given in Figs. 14.19 through 14.21. Note that the times to failure in Fig. 14.20 have an *exponential-like shape*, with the mode (most likely value) near zero. However, the exponential distribution itself does not provide a good model for these data; see the discussion in Sec. 14.4.2. Observe also that the other two histograms have their mode at a positive value and are skewed to the right (i.e., the right tail is longer).

Discrete distributions seem, in general, to be less common than continuous distributions in manufacturing systems. However, two examples of discrete distributions

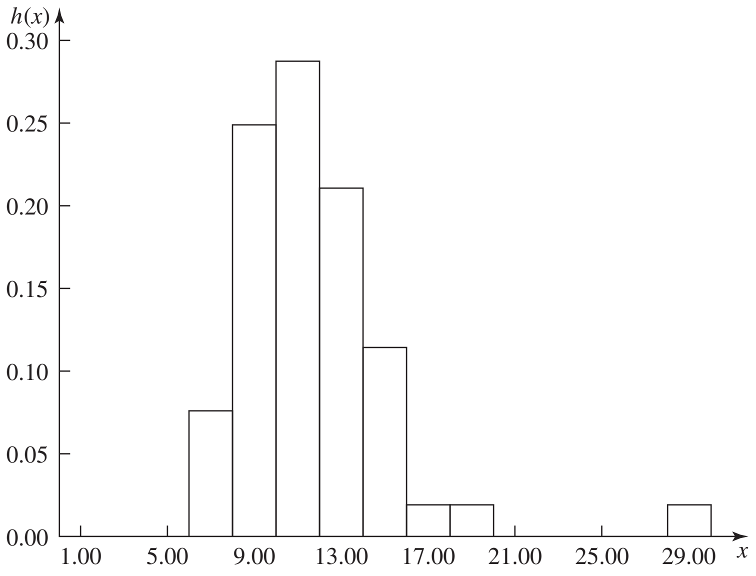


FIGURE 14.19
Histogram of 52 processing times for an automotive manufacturer.

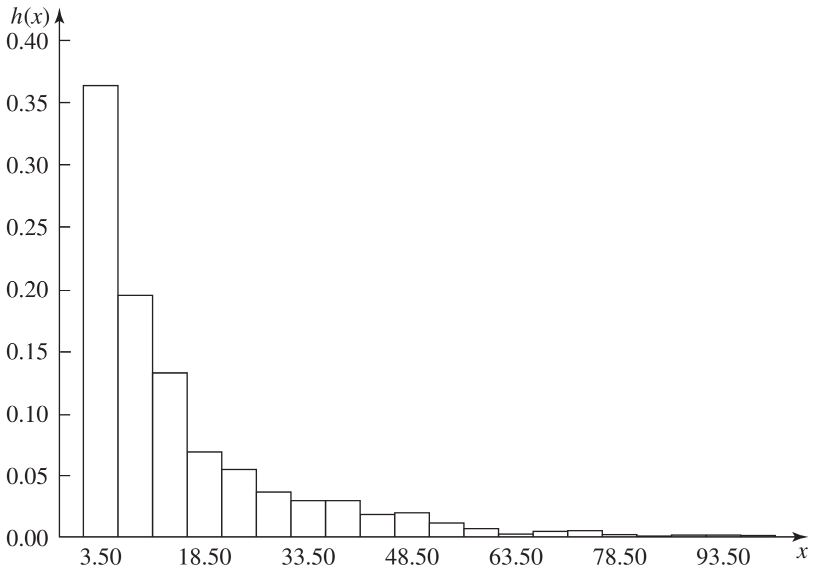


FIGURE 14.20
Histogram of 1603 times to failure for a household-products manufacturer.

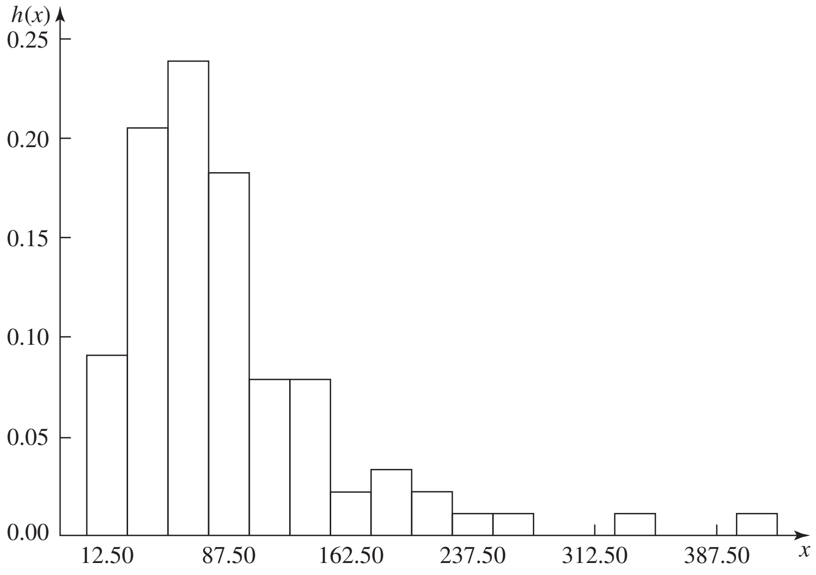


FIGURE 14.21
Histogram of 88 repair times for an aluminum-products manufacturer.

are the outcome of inspecting a part (say, good or bad), and the size of an order arriving to a factory (the possible values are 1, 2, . . .).

14.4.2 Machine Downtimes

The most important source of randomness for many manufacturing systems is that associated with machine breakdowns or unscheduled downtime. Random downtime results from such events as actual machine failures, part jams, and broken tools. The following example illustrates the importance of modeling machine downtime correctly.

EXAMPLE 14.3. A company is going to buy a new machine tool from a vendor who claims that the machine will be down 10 percent of the time. However, the vendor has no data on how long the machine will operate before breaking down or on how long it will take to repair the machine. Some simulation analysts have accounted for random breakdowns by simply reducing the machine processing rate by 10 percent. We will see, however, that this can produce results that are quite inaccurate.

Suppose that the single-machine-tool system (see, for example, Example 4.32) will *actually* operate according to the following assumptions *when installed* by the purchasing company:

- Jobs arrive with exponential interarrival times with a mean of 1.25 minutes.
- Processing times for a job at the machine are a constant 1 minute.
- The times to failure for the machine have an exponential distribution (based on *calendar* time, as discussed later) with mean 540 minutes (9 hours).

TABLE 14.2
Simulation results for the single-machine-tool system

Measure of performance	Breakdowns mean = 540 minutes	Breakdowns mean = 54 minutes	No breakdowns
Average throughput per week*	1908.8	1913.8	1914.8
Average time in system*	35.1	10.3	5.6
Maximum time in system†	256.7	76.1	39.1
Average number in queue*	27.2	7.3	3.6
Maximum number in queue†	231.0	67.0	35.0

* Average over five runs.
† Maximum over five runs.

- The repair times for the machine have a gamma distribution (shape parameter equal to 2) with mean 60 minutes (1 hour).
- The machine is, thus, broken 10 percent of the time, since the mean length of the up–down cycle is 10 hours.

In column 2 of Table 14.2 are results from five independent simulation runs of length 160 hours (20 eight-hour days) for the above system; all times are in minutes. In column 4 of the table are results from five simulation runs of length 160 hours for the machine-tool system *with no breakdowns*, but with the processing (cycle) rate reduced from 1 job per minute to 0.9 job per minute, as has sometimes been the approach in practice.

Note first that the average weekly throughput is almost identical for the two simulations. [For a system with no capacity shortages (see Prob. 14.1) that is simulated for a *long period of time*, the average throughput for a 40-hour week must be equal to the arrival rate for a 40-hour week, which is 1920 here.] On the other hand, note that measures of performance such as average time in system for a job and maximum number of jobs in queue are vastly different for the two cases. Thus, the *deterministic* adjustment of the processing rate produces results that differ greatly from the *correct* results based on actual breakdowns of the machine.

In column 3 of Table 14.2 are results from five simulation runs of length 160 hours for the machine-tool system *with breakdowns*, but with a mean time to failure of 54 minutes and a mean repair time of 6 minutes; thus, the machine is still broken 10 percent of the time. Note that the average time in system and the maximum number in queue are quite different for columns 2 and 3. Therefore, when explicitly accounting for breakdowns in a simulation model, it is also important to have an accurate assessment of mean time to failure and mean repair time for the actual system.

This example also shows that the required amount of model detail depends on the desired measure of performance. All three models produce accurate estimates of (expected) throughput, but this is clearly not the case for the other performance measures.

Despite the importance of modeling machine breakdowns correctly, as demonstrated by the above example, there has been little discussion of this subject in the simulation literature. Thus, we now discuss modeling random machine downtimes in some detail. Deterministic downtimes such as breaks, shift changes, and scheduled maintenance are relatively easy to model and are not treated here.

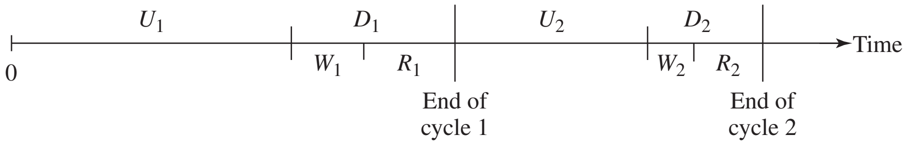


FIGURE 14.22
Up–down cycles for a machine.

A machine goes through a sequence of cycles, with the *i*th cycle consisting of an up ("operating") segment of length U_i followed by a down segment of length D_i. During an up segment, a machine will process parts if any are available and if the machine is not blocked. The first two up–down cycles for a machine are shown in Fig. 14.22. Let B_i and I_i be the amounts of time during U_i that the machine is busy processing parts and that the machine is idle (either starved for parts or blocked by the current finished part), respectively. Thus, $U_i = B_i + I_i$. Note that B_i and I_i may each correspond to a number of separated time segments and, thus, are not represented in Fig. 14.22.

Let W_i be the amount of time from the *i*th "failure" of the machine until its subsequent repair begins, and let R_i be the length of this *i*th repair time. Thus, $D_i = W_i + R_i$, as shown in Fig. 14.22.

We will assume for simplicity that cycles are independent of each other and are probabilistically identical. This implies that each of the six sequences of random variables defined above (e.g., $U_1, U_2, \ldots$ and $D_1, D_2, \ldots$) are IID within themselves (see Prob. 14.2). We will also assume that U_i and D_i are independent for all *i* (see Prob. 14.3).

We now discuss how to model machine-up segments in a simulation model assuming that "appropriate" breakdown data are available. The following two methods are widely used (see also Prob. 14.4):

Calendar Time

Assume that the uptime data $U_1, U_2, \ldots$ are available and that we can fit a standard probability distribution (e.g., exponential) F_U to these data using the techniques of Chap. 6. Alternatively, if no distribution provides a good fit, assume that an empirical distribution is used to model the U_i's. Then, starting at time 0, we generate a random value u_1 from F_U and $0 + u_1 = u_1$ is the time of the first failure of the machine in the simulation. When the machine actually fails at time u_1, note that it may either be busy or idle (see Prob. 14.5). Suppose that d_1 is determined to be the first downtime (to be discussed below) for the machine. Then the machine goes back up at time $u_1 + d_1$. (If the machine was processing a part when it failed at time u_1, then it is usually assumed that the machine finishes this part's *remaining* processing time starting at time $u_1 + d_1$.) At time $u_1 + d_1$, another value u_2 is randomly generated from F_U and the machine is up during the time interval $[u_1 + d_1, u_1 + d_1 + u_2)$. If d_2 is the second downtime, then the machine is down during the time interval $[u_1 + d_1 + u_2, u_1 + d_1 + u_2 + d_2)$, etc.

There are two drawbacks of the *calendar-time approach.* First, it allows the machine to break down when it is idle, which may not be realistic. Also, assume that the machine in question is part of a larger system and has machines both upstream and downstream of it. If we simulate two different versions of the overall system using the F_U distribution to break down the specified machine (and also synchronize the downtimes), then the machine will break down at the same points in simulated (calendar) time for both simulations. However, due to different amounts of starving from the upstream machines and blocking from the downstream machines in the two simulation runs, the specified machine could have significantly less actual busy time for one configuration than for the other. This also may not be very realistic.

Busy Time

Assume that the busy-time data $B_1, B_2, \ldots$ are available and that we can fit a distribution F_B to these data. (Alternatively, an empirical distribution can be used.) Then, starting at time 0, we generate a random value b_1 from F_B. Then the machine is up until its total accumulated *busy* (*processing*) *time* reaches a value of b_1, at which point the *busy* machine fails. (For example, suppose that b_1 is equal to 60.7 minutes and each processing time is a constant 1 minute. Then the machine fails while processing its 61st part.) If f_1 is the simulated time at which the machine fails for the first time ($f_1 \geq b_1$) and d_1 is the first downtime, then the machine goes back up at time $f_1 + d_1$, etc.

In general, the busy-time approach is more natural than the calendar-time approach. We would expect the next time of failure of a machine to depend more on total busy time since the last repair than on calendar time since the last repair. However, in practice, the busy-time approach may not be feasible, since uptime data ($U_1, U_2, \ldots$) may be available but not busy-time data ($B_1, B_2, \ldots$). In many factories, only the times that the machine fails and the times that the machine goes back up (completes repair) are recorded. Thus, the uptimes $U_1, U_2, \ldots$ may be easily computed, but the actual busy times $B_1, B_2, \ldots$ may be unknown (see Prob. 14.6). (In computing the U_i's, time intervals where the machine is off, e.g., idle shifts, should be subtracted out.) Note that if a machine is never starved or blocked, then $B_i = U_i$ and the two approaches are equivalent.

There is a third method that is sometimes used to model machine-up segments in a simulation model, namely, the number of completed parts. For example, after a machine has completed 100 parts, it might be necessary to perform maintenance on the machine.

We now discuss how to model machine-down segments, assuming that factory data are available. Assume first that the waiting time to repair, W_i, for the ith cycle is zero or negligible relative to the repair time R_i (for $i = 1, 2, \ldots$). Then we fit a distribution (e.g., gamma) F_D to the observed downtime data $D_1, D_2, \ldots$. Each time the machine fails, we generate a new random value from F_D and use it as the subsequent downtime (repair time).

Suppose that the W_i's may sometimes be "large," due to waiting for a repairman to arrive. If only D_i's are available (and not the W_i's and R_i's separately), as is often the case in practice, then fit a distribution F_D to the D_i's and randomly sample from F_D each time a downtime is needed in the simulation model. The reader should be aware, however, that F_D is a valid downtime distribution for only the current number of repairmen and the maintenance requirements of the system from which the D_i's were collected.

Finally, assume that the W_i's may be significant and that the W_i's and R_i's are individually available. Then one approach is to model the waiting time for a repairman as a maintenance resource with a finite number of units and to fit a distribution F_R to the R_i's. If a repairman is available when the machine fails, the waiting time is zero unless there is a travel time, and the repair time is generated from F_R. If a repairman is not available, the broken machine joins a queue of machines waiting for a repairman, etc.

Suppose that factory data are not available to support either the calendar-time or busy-time breakdown models previously discussed. This often occurs when simulating a proposed manufacturing facility, but may also be the case for an existing plant when there is inadequate time for data collection and analysis. We now present a *tentative* model for this no-data case, which is likely to be more accurate than many of the approaches used in practice (see Example 14.3).

We will first assume that the amount of machine *busy* time, B, before a failure has a gamma distribution with shape parameter $\alpha_B = 0.7$ and scale parameter β_B to be specified. Note that the exponential distribution (gamma distribution with $\alpha_B = 1.0$) does not appear, in general, to be a good model for machine busy times, even though it is often used in simulation models for this purpose.

EXAMPLE 14.4. In Fig. 14.23 we show the histogram of machine times to failure (actually busy times) from Fig. 14.20 with the best-fitting exponential distribution superimposed over it. It is visually clear that the exponential distribution does not provide

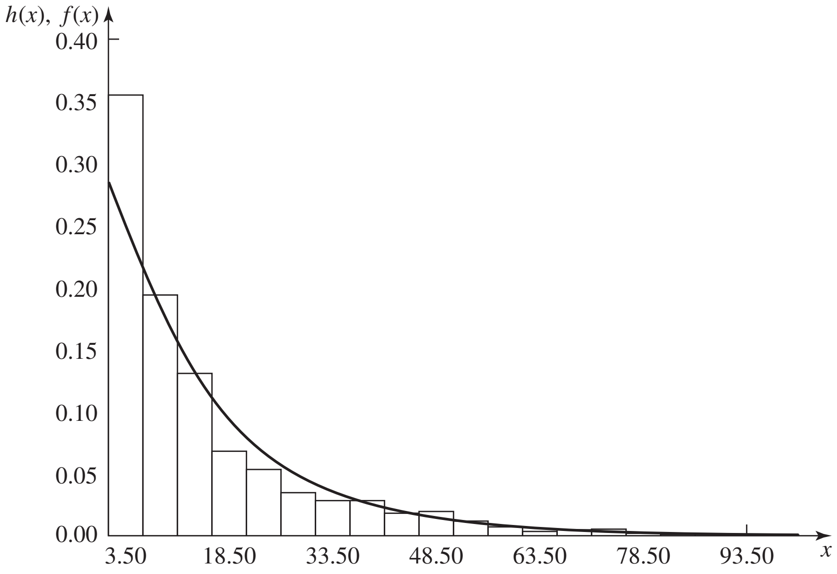


FIGURE 14.23
Density-histogram plot for the time-to-failure data and the exponential distribution.

a very good fit for the data, since its density lies above the histogram for moderate values of x. Furthermore, it was rejected by the goodness-of-fit tests of Sec. 6.6.2.

We chose the gamma distribution because of its flexibility (i.e., its density can assume a wide variety of shapes) and because it has the general shape of many busy-time histograms when $\alpha_B \leq 1$. (The Weibull distribution could also have been used, but its mean is harder to compute.) The particular shape parameter $\alpha_B = 0.7$ for the gamma distribution was determined by fitting a gamma distribution to seven different sets of busy-time data, with 0.7 being the average shape parameter obtained. In only one case was the estimated shape parameter close to 1.0 (the exponential distribution). The density function for a gamma distribution with shape and scale parameters 0.7 and 1.0, respectively, is shown in Fig. 14.24.

We will assume that machine downtime (or repair time) has a gamma distribution with shape parameter $\alpha_D = 1.3$ and a scale parameter β_D to be determined. This particular shape parameter was determined by fitting a gamma distribution to 11 different sets of downtime data, with 1.3 being the average shape parameter obtained. The density function for a gamma distribution with shape and scale parameters 1.3 and 1.0, respectively, is shown in Fig. 14.25. This density function has the same general shape as downtime histograms often experienced in practice (see Fig. 14.21).

In order to complete our model of machine downtimes in the absence of data, we need to specify the scale parameters β_B and β_D. This can be done by soliciting

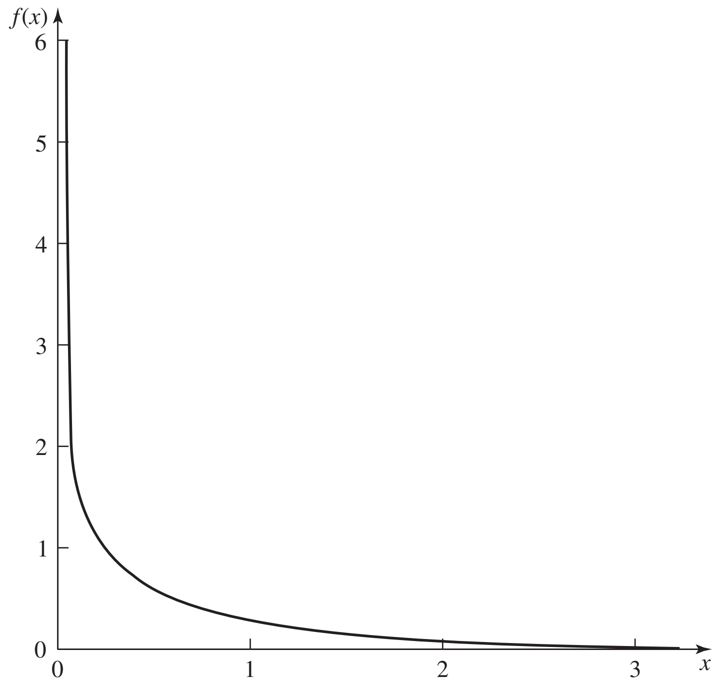


FIGURE 14.24
Gamma(0.7, 1.0) distribution.

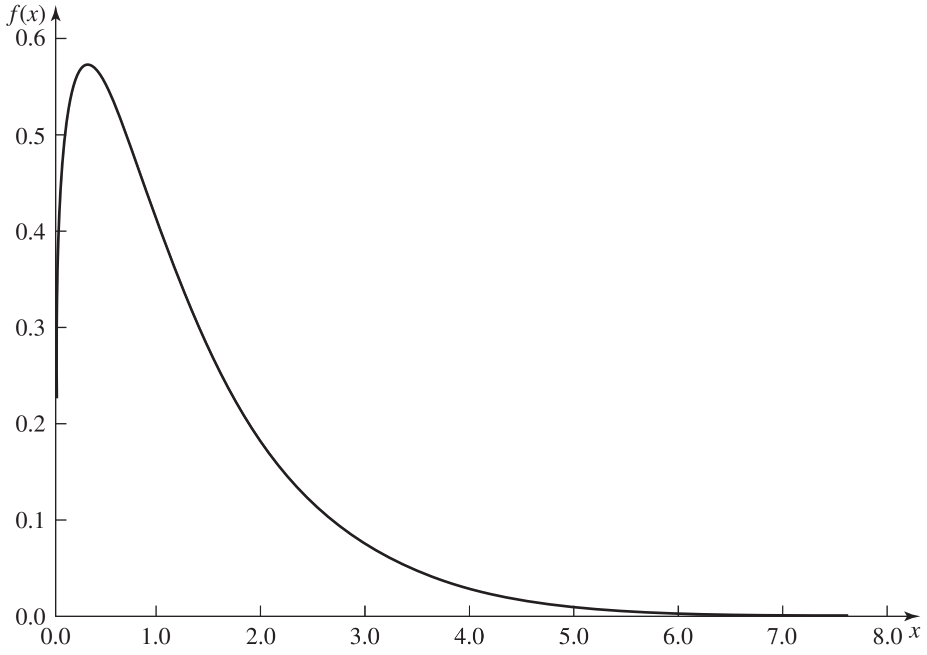


FIGURE 14.25
Gamma(1.3, 1.0) distribution.

two pieces of information from system "experts" (e.g., engineers or vendors). We have found it convenient and typically feasible to obtain an estimate of mean downtime $\mu_D = E(D)$ and an estimate of machine efficiency e, which we now define. The *efficiency* e is defined to be the long-run proportion of potential processing time (i.e., parts present and machine not blocked) during which the machine is actually processing parts, and is given by

$$e = \frac{\mu_B}{\mu_B + \mu_D}$$

where $\mu_B = E(B)$ is the mean amount of machine busy time before a failure. If the machine is never starved or blocked, then $\mu_B = \mu_U = E(U)$ and e is the long-run proportion of time during which the machine is processing parts. Using the values of μ_D and e (and also the fact that the mean of a gamma distribution is the product of its shape and scale parameters), it is easy to show that the required scale parameters are given by

$$\beta_B = \frac{e\mu_D}{0.7(1 - e)}$$

and

$$\beta_D = \frac{\mu_D}{1.3}$$

Thus, our model for machine downtimes when no data are available has been completely specified.

We have discussed above models for the breaking down and repair of machines. However, in practice there are a number of additional complications that often occur, such as multiple independent causes of machine failure. Some of these complexities are discussed in the problems at the end of this chapter.

14.5 AN EXTENDED EXAMPLE

We now illustrate how simulation can be used to improve the performance of a manufacturing system. We will simulate a number of different configurations of a system consisting of workstations and forklift trucks, with the simulation output statistics from one configuration being used to determine the next configuration to be simulated. This procedure will be continued until a system design is obtained that meets our performance requirements.

14.5.1 Problem Description and Simulation Results

A company is going to build a new manufacturing facility consisting of an input/output (or receiving/shipping) station and five workstations as shown in Fig. 14.26. The machines in a particular station are identical, but the machines in different stations are dissimilar. (This system is an embellishment of the job-shop model in Sec. 2.7.) One of the goals of the simulation study is to determine the number of machines needed in each workstation. It has been decided that the distances (in feet)

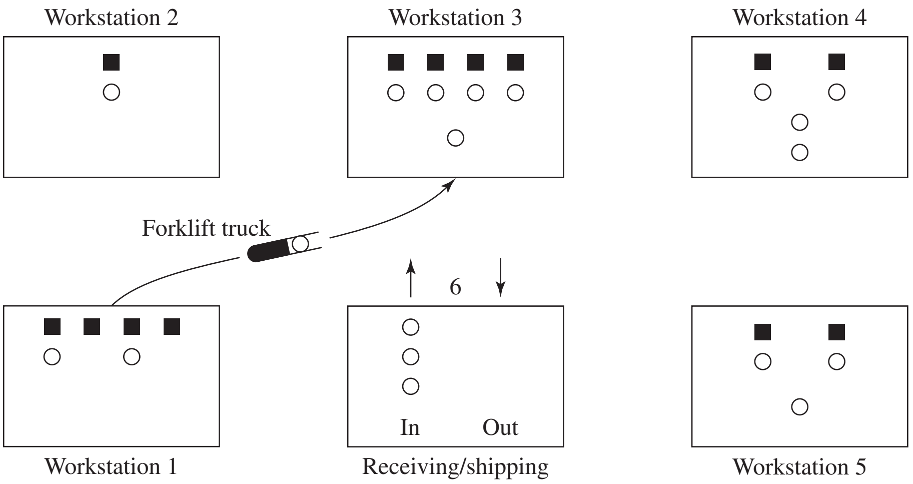


FIGURE 14.26
Layout for the manufacturing system.

TABLE 14.3
Distances (in feet) between the six stations

Station	1	2	3	4	5	6
1	0	150	213	336	300	150
2	150	0	150	300	336	213
3	213	150	0	150	213	150
4	336	300	150	0	150	213
5	300	336	213	150	0	150
6	150	213	150	213	150	0

between the six stations will be as shown in Table 14.3 (the input/output station is numbered 6).

Assume that jobs arrive at the input/output station with interarrival times that are independent exponential random variables with a mean of 1/15 hour. Thus, 15 jobs arrive in a "typical" hour. There are three types of jobs, and jobs are of types 1, 2, and 3, with respective probabilities 0.3, 0.5, and 0.2. Job types 1, 2, and 3 require 4, 3, and 5 operations to be done, respectively, and each operation must be done at a specified workstation in a prescribed order. Each job begins at the input/output station, travels to the workstations on its routing, and then leaves the system at the input/output station. The routings for the different job types are given in Table 14.4.

A job must be moved from one station to another by a forklift truck, which moves at a constant speed of 5 feet per second. Another goal of the simulation study is to determine the number of forklift trucks required. When a forklift becomes available, it processes requests by jobs in increasing order of the distance between the forklift and the requesting job (i.e., the rule is shortest distance first). If more than one forklift is idle when a job requests transport, then the closest forklift is used. When the forklift finishes moving a job to a workstation, it remains at that station if there are no pending job requests (see Prob. 14.12).

If a job is brought to a particular workstation and all machines there are already busy or blocked (see the discussion below), the job joins a single FIFO queue at that station. The time to perform an operation at a particular machine is a gamma random variable with a shape parameter of 2, whose mean depends on the job type and the workstation to which the machine belongs. The mean service time for each job type and each operation is given in Table 14.5. Thus, the mean *total* service time averaged over all jobs is 0.77 hour (see Prob. 14.13). When a machine finishes processing

TABLE 14.4
Routings for the three job types

Job type	Workstations in routing
1	3, 1, 2, 5
2	4, 1, 3
3	2, 5, 1, 4, 3

TABLE 14.5
Mean service time for each job type and each operation

Job type	Mean service time for successive operations (hours)
1	0.25, 0.15, 0.10, 0.30
2	0.15, 0.20, 0.30
3	0.15, 0.10, 0.35, 0.20, 0.20

a job, the job blocks that machine (i.e., the machine cannot process another job) until the job is removed by a forklift (see Prob. 14.14).

We will simulate the proposed manufacturing facility to determine how many machines are needed at each workstation and how many forklift trucks are needed to achieve an expected throughput of 120 jobs per 8-hour day, which is the maximum possible (see Prob. 14.15). Among those system designs that can achieve the desired throughput, the best system design will be chosen on the basis of measures of performance such as average time in system, maximum input queue sizes, proportion of time each workstation is busy, proportion of time the forklift trucks are moving, etc.

For each proposed system design, 10 replications of length 920 hours will be made (115 eight-hour days), with the first 120 hours (15 days) of each replication being a warmup period. (See Sec. 14.5.2 for a discussion of warmup-period determination.) We will also use the method of common random numbers (see Sec. 11.2) to simulate the various system designs. This will guarantee that a particular job will arrive at the same point in time, be of the same job type, and have the same sequence of service-time values for all system designs on a particular replication. Job characteristics will, of course, be different on different replications.

To determine a starting point for our simulation runs (i.e., to determine system design 1), we will do a simple queueing-type analysis of our system. In particular, for workstation i (where $i = 1, 2, \ldots, 5$) to be well defined (have sufficient processing capacity) in the long run, its utilization factor $\rho_i = \lambda_i/(s_i\omega_i)$ (see App. 1B for notation) must be less than 1. For example, the arrival rate to station 1 is $\lambda_1 = 15$ per hour, since all jobs visit station 1. Using conditional probability [see, for example, Ross (2003, chap. 3)], the mean service time at station 1 is

$$0.3(0.15 \text{ hour}) + 0.5(0.20 \text{ hour}) + 0.2(0.35 \text{ hour}) = 0.215 \text{ hour}$$

which implies that the service rate (per machine) at station 1 is $\omega_1 = 4.65$ jobs per hour. Therefore, if we solve the equation $\rho_1 = 1$, we obtain that the required number of machines at station 1 is $s_1 = 3.23$, which we round up to 4. (What is wrong with this analysis? See Prob. 14.16.) A summary of the calculations for all five stations is given in Table 14.6, from which we see that 4, 1, 4, 2, and 2 machines are *supposedly* required for stations 1, 2, . . . , 5, respectively.

We can do a similar analysis for forklifts. Type 1 jobs arrive to the system at a rate of 4.5 (0.3 times 15) jobs per hour. Furthermore, the mean *travel* time for a type 1 job is 0.06 hour (along the route 6–3–1–2–5–6). Thus, 0.27 forklift will be required to move type 1 jobs. Similarly, 0.38 and 0.24 forklift will be required for

TABLE 14.6
Required number of machines for each workstation

Workstation	Arrival rate (jobs/hour)	Service rate [(jobs/hour)/machine]	Required number of machines
1	15.0	4.65	$3.23 \rightarrow 4$
2	7.5	8.33	$0.90 \rightarrow 1$
3	15.0	3.77	$3.98 \rightarrow 4$
4	10.5	6.09	$1.72 \rightarrow 2$
5	7.5	4.55	$1.65 \rightarrow 2$

TABLE 14.7
Required number of forklift trucks

Job type	Arrival rate (jobs/hour)	Mean travel time [(hour/job)/forklift]	Required number of forklifts
1	4.5	0.06	0.27
2	7.5	0.05	0.38
3	3.0	0.08	0.24
All			$0.89 \rightarrow 1$

type 2 and type 3 jobs, respectively. Thus, a total of 0.89 forklift is required, which we round up to 1. (What is missing from this analysis? See Prob. 14.17.) A summary of the forklift calculations is given in Table 14.7, from which we see that the mean travel time averaged over all job types is 0.06 hour.

A summary of the 10 simulation runs for system design 1, which was specified by the above analysis, is given in Table 14.8 (all times are in hours). Note, for example, that the average utilization (proportion of time busy) of the four machines in

TABLE 14.8
Simulation results for system design 1

Number of machines: 4, 1, 4, 2, 2
Number of forklifts: 1

Station / Performance measure	1	2	3	4	5
Proportion machines busy	0.72	0.74	0.83	0.73	0.66
Proportion machines blocked	0.21	0.26	0.17	0.27	0.33
Average number in queue	3.68	524.53	519.63	569.23	32.54
Maximum number in queue	32.00	1072.00	1026.00	1152.00	137.00
Average daily throughput		94.94			
Average time in system		109.20			
Average total time in queues		107.97			
Average total wait for transport		0.42			
Proportion forklifts moving loaded		0.77			
Proportion forklifts moving empty		0.22			

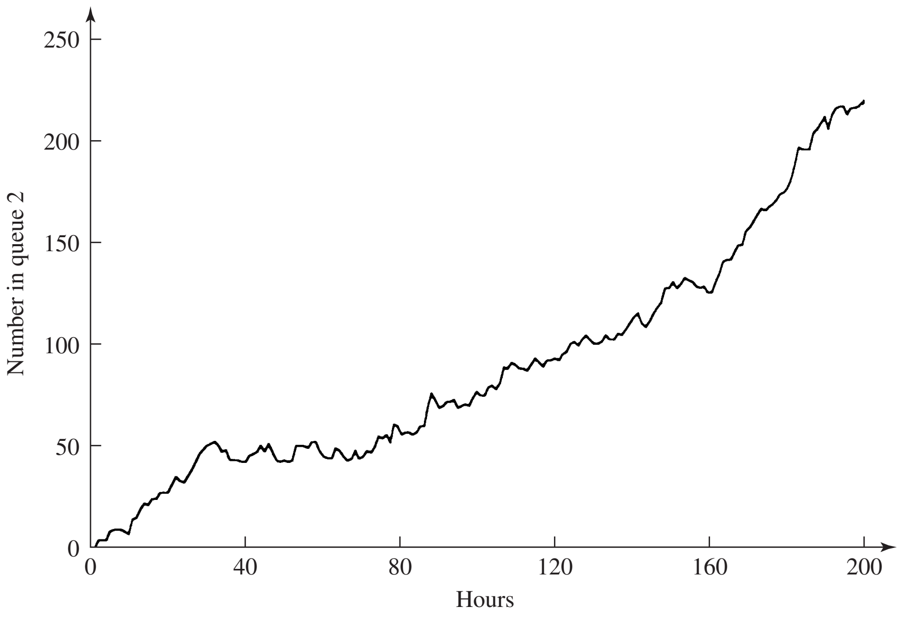


FIGURE 14.27
Number in queue 2 in time increments of 1 hour for system design 1 (replication 1).

station 1 (over the 10 runs) is 0.72, the time-average number of jobs in the queue feeding station 1 is 3.68, and the maximum number of jobs in this queue (over the 10 runs) is 32. More important, observe that the average daily throughput is 94.94, which is much less than the expected throughput of 120 for a well-defined system; it follows that this design must suffer from capacity shortages (i.e., machines or forklifts). The average time in system for a job is 109.20 hours (107.97 hours for *all* queues visited and 0.42 hour for *all* transporter waits), which is excessive given that the mean total service time is less than 1 hour. Note that the *total* forklift utilization is 0.99. The high forklift utilization along with the large machine-blockage proportions strongly suggest that one or more additional forklifts are needed. Finally, observe that stations 2, 3, and 4 are each either busy or blocked 100 percent of the time, and their queue statistics are quite large. (See also Fig. 14.27, where the number in queue 2 is plotted in time increments of 1 hour for the first 200 hours of replication 1.) We will therefore add a single machine to each of stations 2, 3, and 4. (We will not add a forklift at this time, although it certainly seems warranted; see system design 3.)

The results from simulating system design 2 (4, 2, 5, 3, and 2 machines for stations 1, 2, . . . , 5 and 1 forklift) are given in Table 14.9. The average daily throughput has gone from 94.94 to 106.77, but is still considerably less than that expected for a well-defined system. Likewise the average time in system has been reduced from 109.20 to 55.84 hours. Even though we added three machines to the system, the queue statistics at station 5 have actually become considerably worse. (Why? See Prob. 14.20.) In fact, station 5 is now busy or blocked 100 percent of the time. Also, the blockage proportions have increased for four out of the five stations.

TABLE 14.9
Simulation results for system design 2

Number of machines: 4, 2, 5, 3, 2
Number of forklifts: 1

Station / Performance measure	1	2	3	4	5
Proportion machines busy	0.75	0.45	0.76	0.54	0.66
Proportion machines blocked	0.25	0.26	0.23	0.30	0.34
Average number in queue	106.04	0.53	46.15	1.17	747.33
Maximum number in queue	364.00	11.00	182.00	17.00	1521.00
Average daily throughput		106.77			
Average time in system		55.84			
Average total time in queues		54.34			
Average total wait for transport		0.69			
Proportion forklifts moving loaded		0.84			
Proportion forklifts moving empty		0.16			

This example reinforces the statement that it may not be easy to predict the effect of local changes on systemwide behavior. Since the total forklift utilization is 1.00, we now add a second forklift to the system.

The results from simulating system design 3 (4, 2, 5, 3, and 2 machines and 2 forklifts) are given in Table 14.10. The average daily throughput is now 120.29, which is not significantly different from 120 as shown in Sec. 14.5.2. *Thus, system design 3 is apparently stable in the long run.* In addition, the average time in system has been decreased from 55.84 to 1.76 hours. Notice also that the average total utilization of the two forklifts is an acceptable 0.71 (see Prob. 14.21), and the station blockage proportions are now small. Finally, the statistics for all five stations

TABLE 14.10
Simulation results for system design 3

Number of machines: 4, 2, 5, 3, 2
Number of forklifts: 2

Station / Performance measure	1	2	3	4	5
Proportion machines busy	0.81	0.45	0.80	0.58	0.83
Proportion machines blocked	0.06	0.06	0.04	0.06	0.07
Average number in queue	3.37	0.24	2.18	0.47	6.65
Maximum number in queue	39.00	10.00	27.00	17.00	85.00
Average daily throughput		120.29			
Average time in system		1.76			
Average total time in queues		0.86			
Average total wait for transport		0.08			
Proportion forklifts moving loaded		0.44			
Proportion forklifts moving empty		0.27			

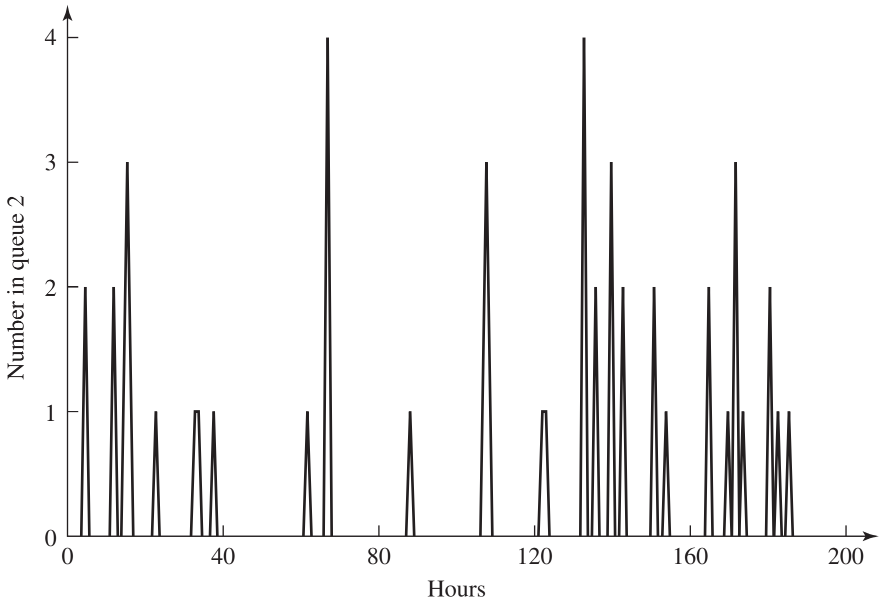


FIGURE 14.28
Number in queue 2 in time increments of 1 hour for system design 3 (replication 1).

seem reasonable (see also Fig. 14.28), with the possible exception of the maximum queue sizes for stations 1 and 5. Whether queue sizes of 39 and 85 are acceptable depends on the particular application. These maximum queue sizes could be made smaller by adding additional machines to stations 1 and 5, respectively. Finally, note that average time in system (1.761) is equal to the sum of average total time in queues (0.861), average total wait for transport (0.075), average transport time (0.059), and average total service time (0.766)—the last two times are not shown in Table 14.10.

In going from system design 1 to system design 2, we added machines to stations 2, 3, and 4 simultaneously. Therefore, it is reasonable to ask whether all three machines are actually necessary to achieve an expected throughput of 120. We first removed one machine from station 2 for system design 3 (total number of machines is now 15) and obtained an average daily throughput of 119.38, which is significantly different from 120 (see Sec. 14.5.2 for the methodology used). Thus, two machines are required for station 2. Next, we removed one machine from station 3 for system design 3 (total number of machines is 15) and obtained an average daily throughput of 115.07, which is once again significantly different from 120. Thus, we need five machines for station 3. Finally, we removed one machine from station 4 for system design 3 and obtained system design 4, whose simulation results are given in Table 14.11. The throughput is unchanged, but the average time in system has increased from 1.76 to 2.61. This latter difference is statistically significant as shown in Sec. 14.5.2. Note also that the average and maximum numbers in queue for station 4 are larger for system design 4, as expected.

TABLE 14.11
Simulation results for system design 4

Number of machines: 4, 2, 5, 2, 2
Number of forklifts: 2

Station / Performance measure	1	2	3	4	5
Proportion machines busy	0.81	0.45	0.80	0.87	0.83
Proportion machines blocked	0.06	0.06	0.04	0.08	0.07
Average number in queue	2.89	0.25	1.88	14.31	6.50
Maximum number in queue	32.00	11.00	27.00	90.00	81.00
Average daily throughput		120.29			
Average time in system		2.61			
Average total time in queues		1.72			
Average total wait for transport		0.07			
Proportion forklifts moving loaded		0.44			
Proportion forklifts moving empty		0.27			

System designs 3 and 4 both seem to be stable in the long run. The design that is preferable depends on factors such as the cost of an additional machine for station 4 (design 3), the cost of extra floor space (design 4), the cost associated with a larger average time in system (design 4), and the cost associated with a larger average work-in-process (design 4).

We now consider another variation of system design 3. It involves, for the first time, a change in the control logic for the system. In particular, jobs waiting for the forklifts are processed in a FIFO manner, rather than shortest distance first as before. The results for system design 5 are given in Table 14.12. Average time

TABLE 14.12
Simulation results for system design 5

Number of machines: 4, 2, 5, 3, 2
Number of forklifts: 2
FIFO queue for forklifts

Station / Performance measure	1	2	3	4	5
Proportion machines busy	0.81	0.45	0.80	0.58	0.83
Proportion machines blocked	0.08	0.08	0.06	0.08	0.08
Average number in queue	4.77	0.29	2.70	0.58	8.28
Maximum number in queue	51.00	11.00	33.00	17.00	95.00
Average daily throughput		120.33			
Average time in system		2.03			
Average total time in queues		1.11			
Average total wait for transport		0.10			
Proportion forklifts moving loaded		0.44			
Proportion forklifts moving empty		0.31			

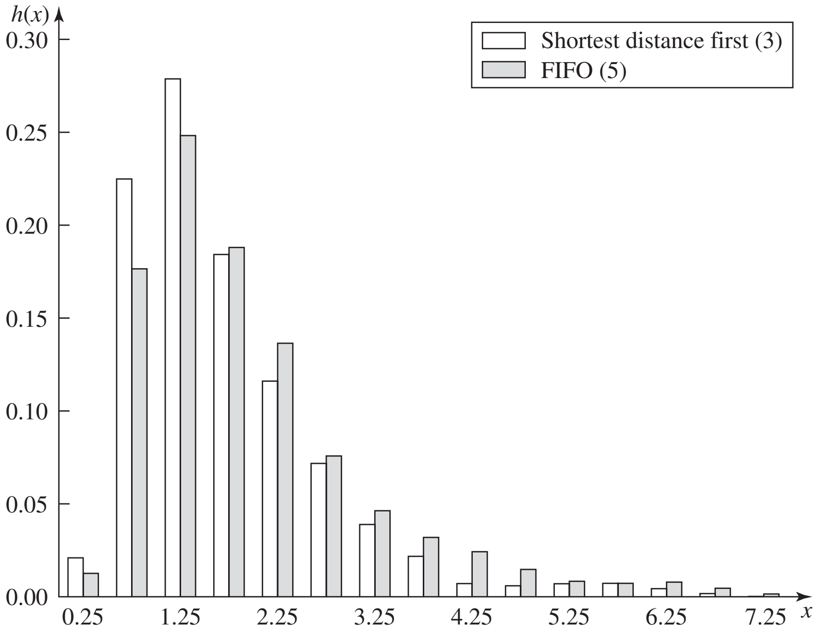


FIGURE 14.29
Histograms of time in system for system designs 3 and 5.

in system has gone from 1.76 to 2.03 hours, an apparent 15 percent increase. (Histograms of time in system for system designs 3 and 5, based on all 10 runs of each, are given in Fig. 14.29.) The queue statistics for station 1 have also increased by an appreciable amount, and the forklifts now spend more time moving empty. It takes a forklift more time to get to a waiting job, since the closest one is not generally chosen. We therefore do *not* recommend the new forklift-dispatching rule.

Finally, we discuss another variation of system design 3 (shortest-distance-first forklift-dispatching rule), where certain machines break down. In particular, we assume that each machine in stations 1 and 5 breaks down independently with an efficiency of 0.9 (see Sec. 14.4.2). The amount of busy time that a machine operates before failure is exponentially distributed with a mean of 4.5 hours, and repair times have a gamma distribution with a shape parameter of 2 and a mean of 0.5 hour. The simulation output for the resulting system design 6 is given in Table 14.13. The average daily throughput is now 119.88, but this is *not* significantly different from 120 (see Sec. 14.5.2). On the other hand, average time in system has gone from 1.76 to 5.31, an increase of 202 percent. The queue statistics for stations 1 and 5 are also appreciably larger. Thus, breaking down only stations 1 and 5 caused a significant degradation in system performance; breaking down all five stations would probably have an even greater impact. In summary, we have once again seen the importance of modeling machine breakdowns correctly.

TABLE 14.13
Simulation results for system design 6

Number of machines: 4, 2, 5, 3, 2
Number of forklifts: 2
Machines in stations 1 and 5 have efficiencies of 0.9

Station / Performance measure	1	2	3	4	5
Proportion machines busy	0.81	0.45	0.80	0.58	0.82
Proportion machines blocked	0.06	0.06	0.04	0.06	0.07
Proportion machines down	0.09	0.00	0.00	0.00	0.09
Average number in queue	16.55	0.25	2.15	0.49	46.73
Maximum number in queue	111.00	11.00	32.00	14.00	262.00
Average daily throughput		119.88			
Average time in system		5.31			
Average total time in queues		4.37			
Average total wait for transport		0.07			
Proportion forklifts moving loaded		0.44			
Proportion forklifts moving empty		0.27			

14.5.2 Statistical Calculations

In this section we perform some statistical calculations related to the manufacturing system of Sec. 14.5.1. We begin by constructing a 90 percent confidence interval for the steady-state mean daily throughput for system design 3, ν_3, using the replication/deletion approach of Sec. 9.5.2. Let

$$X_j = \text{average throughput on days 16 through 115 on replication } j \text{ for } j = 1, 2, \ldots, 10$$

where the warmup period is $l = 15$ days or 120 hours. Then the desired confidence interval is

$$120.29 \pm t_{9,\,0.95}\sqrt{\frac{1.20}{10}} \qquad \text{or} \qquad 120.29 \pm 0.63$$

which contains 120. Similarly, we get the following 90 percent confidence interval for the steady-state mean daily throughput for system design 6, ν_6:

$$119.88 \pm t_{9,\,0.95}\sqrt{\frac{0.60}{10}} \qquad \text{or} \qquad 119.88 \pm 0.45$$

which also contains 120.

System designs 3 and 4 are both well defined in the sense of having steady-state mean daily throughputs that cannot be distinguished from 120. However, our estimates of the steady-state mean time in system for these system designs are 1.76 and 2.61, respectively, which *appear* to be somewhat different. To see if this difference is statistically significant, we construct a 90 percent confidence interval for $\nu'_3 - \nu'_4$

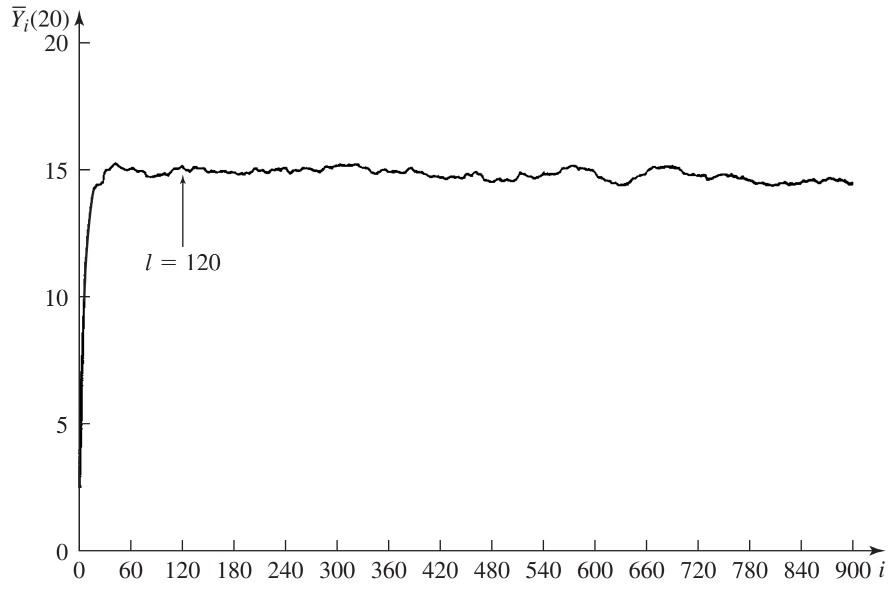


FIGURE 14.30
Moving average ($w = 20$) of hourly throughputs for system design 3.

using the replication/deletion approach (see Example 10.5), where ν_i' is the steady-state mean time in system for system design i (where $i = 3, 4$). We get

$$-0.85 \pm t_{9,\,0.95}\sqrt{\frac{0.22}{10}} \qquad \text{or} \qquad -0.85 \pm 0.27$$

which does not contain 0. Thus, ν_3' *is* significantly different from ν_4'.

The results presented in Sec. 14.5.1 (and here) assume a warmup period of 120 hours or 15 days. This warmup period was obtained by applying Welch's procedure (Sec. 9.5.1) to the 920 hourly throughputs in each of the 10 replications for system design 3 (where Y_{ji} is the throughput in the ith hour of the jth run). The moving average $\overline{Y}_i(20)$ (using a window of $w = 20$) is plotted in Fig. 14.30, from which we obtained a warmup period of $l = 120$ hours. We performed similar analyses for system designs 4, 5, and 6, and a warmup period of 120 hours seemed adequate for these systems as well.

14.6 A SIMULATION CASE STUDY OF A METAL-PARTS MANUFACTURING FACILITY

In this section we describe the results of a successful simulation study of a manufacturing and warehousing system [see Law and McComas (1988)]. The facility described is fictitious for reasons of confidentiality, but is similar to the system actually

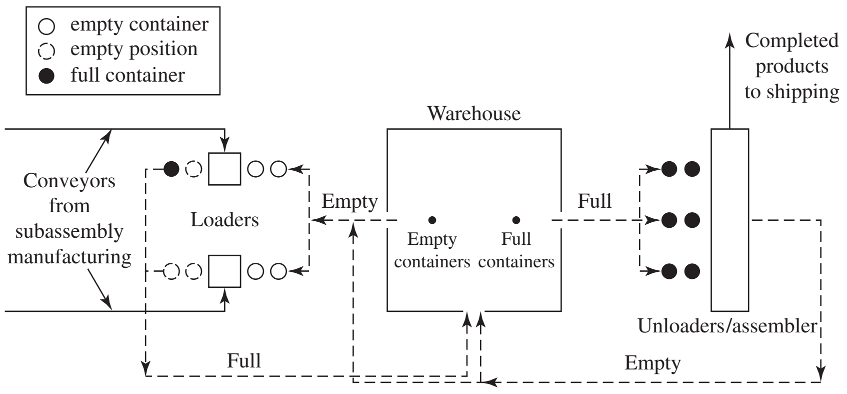


FIGURE 14.31
Layout of the system.

modeled for a Fortune 500 company. The project objectives, the simulation steps, and the benefits that we describe are also very similar to the actual ones.

14.6.1 Description of the System

The manufacturing facility (see Fig. 14.31) produces several different metal parts, each requiring three distinct subassemblies. Subassemblies corresponding to a particular part are produced in large batches on one of two subassembly manufacturing lines, and then moved by conveyor to a loader where they are placed into empty containers. Each container holds only one type of subassembly at a time. The containers are stored in a warehouse until all three of the part subassemblies are available for assembly. Containers of the three subassemblies corresponding to a particular part are brought to an unloader/assembler (henceforth called the assembler), where they are unloaded and assembled into the final product, which is then sent to shipping. The resulting empty containers are temporarily stored in a finite-capacity accumulating conveyor (not shown in the figure) at the back of the assembler. They are then taken to the loaders, if needed; otherwise, they are transported to the warehouse. Full and empty containers are moved by forklift trucks.

The assembler operates only 5 days a week, while the remainder of the system is in operation three shifts a day for 7 days a week. Also, the subassembly lines, the loaders, and the assembler are subject to random breakdowns.

14.6.2 Overall Objectives and Issues to Be Investigated

The subassembly lines already existed at the time of the study. However, the loaders, the warehouse, and the assembler were in the process of being designed. (They were to replace existing technology that had certain throughput limitations.) As a result, the major objectives of the study were to see if the proposed system components would interact with each other effectively to produce the desired throughput, and also to determine the optimal system resource levels, such as the number of containers.

The specific issues investigated in the study included the following:

- Number of containers required
- Number of forklift trucks required and their control logic
- Number of "staged" containers desired in the input queues of the loaders and the assembler (cannot be exceeded)
- Number of output queue positions for the loaders
- Number of required shifts for the assembler

Containers are staged in an input queue to keep the corresponding machine from becoming starved. In the case of a starved loader, the attached subassembly line is also stopped. If the output queue for a loader is full when a container completes being loaded, then the loader is blocked and the corresponding subassembly line is also stopped.

14.6.3 Development of the Model

The study described here took 3 person-months to complete. An important part of the model-building process was the following series of meetings:

- Three-day initial meeting to define project objectives, delineate model assumptions, and specify data requirements
- One-day meeting (before programming) to perform a structured walk-through of the model assumptions (see Sec. 5.4.3) before an audience of the client's engineers and managers
- One-day meeting to review initial simulation results and to make changes to model assumptions

As a result of the initial meeting, the company supplied us with a large amount of data that already existed in its computer databases and reports; however, a significant effort was required by both parties to get the data into a usable format. The UniFit statistical package (the predecessor of ExpertFit as described in Sec. 6.7) was used to analyze the data and to determine the appropriate probability distribution for each source of system randomness. Highlights of our findings are given in Table 14.14. In some cases standard distributions such as lognormal or Weibull were used; in other cases, an empirical distribution (see Sec. 6.2.4) based on the actual data was necessary.

The simulation model was programmed in the SIMAN (the predecessor of Arena as discussed in Sec. 3.5.1) simulation package, although other simulation packages could have been used as well. SIMAN was selected because of its flexibility and material-handling features. The model consisted of approximately 2000 lines of code, 75 percent of which consisted of FORTRAN event routines. This model

TABLE 14.14
Probability distributions for the model

Source of randomness	Distribution type
Subassembly line busy times	Empirical
Subassembly line repair times	Empirical
Subassembly line setup times	Triangular
Loader busy times	Empirical
Loader repair times	Lognormal
Assembler busy times	Weibull
Assembler repair times	Lognormal
Assembler setup times	Uniform

complexity was necessitated by a complicated set of rules (not described here) for *each* part that specify when its corresponding subassemblies are sent to the assembler.

14.6.4 Model Verification and Validation

Verification is concerned with determining if the simulation computer program is working as intended, and the initial verification efforts included the following:

- The model was programmed and debugged in steps.
- An interactive debugger was used to verify that each program path was correct.
- Model output results were checked for reasonableness.
- Model summary statistics for the values generated from the input probability distributions were compared with historical-data summary statistics.

In addition, two more "definitive" verification checks were performed. From the historical average busy times and average repair times, it was possible to compute the theoretical efficiency (see Sec. 14.4.2) for each line. These efficiencies and comparable ones produced by the simulation model (for scenario 1 in Table 14.17) are given in Table 14.15. The closeness of the efficiencies indicates that the program for the subassembly lines was probably correct.

Using the simulation efficiencies from Table 14.15 and three shifts for the assembler, it was possible to compute a theoretical efficiency of 0.643 for the assembler. On the other hand, the simulation model actually produced an assembler efficiency of 0.630. The closeness of these two efficiencies indicates that the program for the assembler is probably correct.

TABLE 14.15
Verification comparison of subassembly-line efficiencies

Line	Theoretical efficiency	Simulation efficiency
1	0.732	0.741
2	0.724	0.727

TABLE 14.16
Validation comparison of subassembly line efficiencies

Line	Historical efficiency	Simulation efficiency
1	0.738	0.741
2	0.746	0.727

Validation is concerned with determining how closely the simulation model represents the actual system, and the following were some of the validation procedures performed:

- All model assumptions were reviewed and agreed upon by company personnel.
- Different data sets for the same type of randomness (e.g., subassembly busy times for the two lines) were tested for homogeneity and merged only if appropriate (see Sec. 6.13).
- All fitted probability distributions (e.g., lognormal) were tested for correctness using the techniques of Chap. 6.

It is generally impossible to validate a simulation model completely, since some part of the actual system will not currently exist. However, building a simulation model of a similar existing system and comparing model and system outputs will often be the most definitive validation technique available. In our case, the subassembly lines were already in operation, while the rest of the system was in the design phase. In Table 14.16 is a comparison for each subassembly line of the historical efficiency and the simulation efficiency. The historical efficiencies were taken from *system output data* available in a company report and were not used in building the model. (The theoretical efficiencies in Table 14.15 were computed from historical *system input data*.) The agreement of the efficiencies in Table 14.16 indicates that the model of the subassembly lines is "valid."

14.6.5 Results of the Simulation Experiments

We first simulated seven different scenarios (system designs), which are described in Table 14.17. Each of these scenarios assumed 3000 containers and used the following company-specified priority rule for dispatching forklift trucks:

1. Take empty containers to loaders.
2. Pick up full containers from loaders.
3. Take full containers to assembler.
4. Pick up empty containers from assembler.

Five independent simulation runs were made for each scenario, with each run being 23 weeks in length and having a 3-week warmup period during which no statistics were gathered. The length of the warmup period was determined by plotting the average number of empty containers (over the five runs) in time increments of 1 hour for scenario 1, which is shown in Fig. 14.32; initially, all containers were empty. Note that this empty-containers stochastic process does not have a steady-state

TABLE 14.17
Scenarios for the initial simulation runs

Scenario	Forklift trucks	Queue sizes	Assembler shifts
1	3	2	3
2	3	2	2
3	2	2	3
4	3	1	3
5	3	3	3
6	3, 2 (weekend)	2	3
7	3	2	2 (all 7 days)

distribution for scenarios 1 through 6 because the assembler does not operate on weekends. What about scenario 7 (see Prob. 14.25)?

A summary (average across the five runs) of the seven sets of simulation runs appears in Table 14.18. Note that the throughput (in parts per week) for scenario 2 (two shifts) is considerably less than that for scenario 1 (three shifts). Also, scenario 2 has a high starvation proportion for the loaders. These results are due to a shortage of empty containers for scenario 2 caused by the assembler not operating enough. Observe for scenario 3 (two forklift trucks) that the throughput is again less than that for scenario 1 and, in addition, the blockage proportion is high for the assembler. This is due to the unavailability of forklift trucks to remove empty containers from the assembler's conveyor caused by the nonoptimal priority rule (i.e., pick up at the assembler has the lowest priority); see Table 14.20. Note that queue sizes of one (scenario 4) cause a small degradation in throughput. Finally, the high forklift-truck

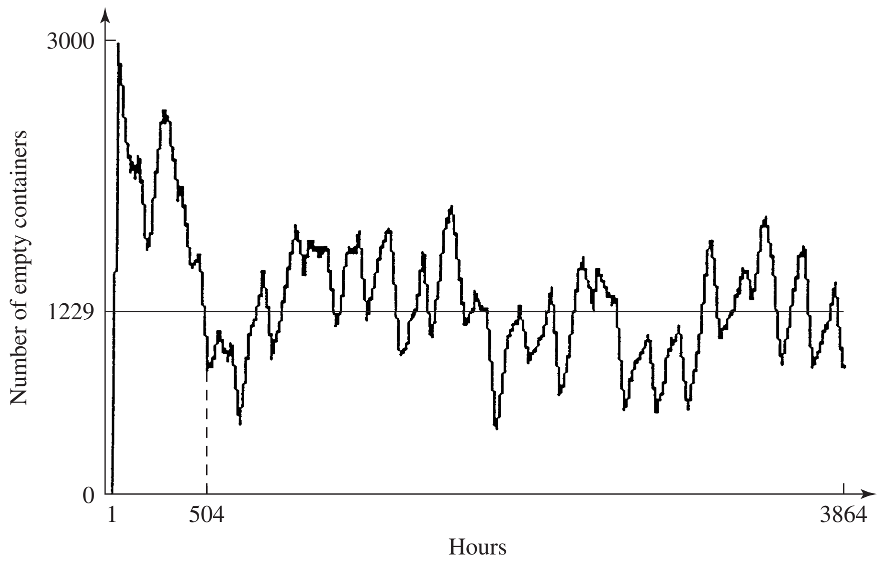


FIGURE 14.32
Average number of empty containers (over the five runs) in time increments of 1 hour for scenario 1.

TABLE 14.18
Summary of simulation results for initial set of runs

Scenario	Avg. empty containers	Parts per week	Loader starved	Assembler blocked	Forklift idle
1	1229	15,019	0.000	0.001	0.370
2	241	11,405	0.157	0.001	0.489
3	442	13,109	0.050	0.133	0.210
4	1218	14,666	0.001	0.001	0.381
5	1233	15,050	0.000	0.001	0.386
6	1234	15,050	0.000	0.001	0.317
7	1123	15,079	0.000	0.001	0.369

idle proportions in Table 14.18 are caused by the periods of inactivity for the loaders and the assembler.

The system description and simulation results described above were presented to approximately 20 of the company's employees including the plant manager. As a result of this meeting, it was decided to simulate the six additional scenarios described in Table 14.19. Each of these scenarios had queue sizes of 2, three assembler shifts, and the same run length and number of runs as before.

A summary of the simulation results for these scenarios (and also scenario 1 from Table 14.18) is given in Table 14.20. Note that the throughput does not change significantly when the number of containers is varied between 2250 and 3000. This can be seen more clearly in Fig. 14.33, where throughput is plotted as a function of the number of containers. Observe also that the shortest-distance-first dispatching rule (scenario 13) gives somewhat better results for two forklift trucks than the original rule (compare scenarios 13 and 3).

14.6.6 Conclusions and Benefits

Based on the simulation results presented above and several conversations with the client, the following project conclusions were reached:

- The company will probably buy 2250 containers rather than the 3000 containers originally budgeted.
- Three assembler shifts (Monday through Friday) are required.

TABLE 14.19
Scenarios for the second set of simulation runs

Scenario	Number of containers	Forklift trucks
8	2750	3
9	2500	3
10	2250	3
11	2000	3
12	1750	3
13	3000	2*

* Dispatching rule is shortest distance first.

TABLE 14.20
Summary of simulation results for second set of runs

Scenario	Avg. empty containers	Parts per week	Loader starved	Assembler blocked	Forklift idle
1	1229	15,019	0.000	0.001	0.370
8	941	14,959	0.006	0.001	0.379
9	640	14,798	0.014	0.001	0.384
10	402	14,106	0.053	0.001	0.411
11	209	11,894	0.192	0.000	0.487
12	80	8758	0.374	0.000	0.597
13	1410	14,306	0.005	0.002	0.265

- Two or three forklift trucks are required for Monday through Friday (further investigation is needed), and two are required for Saturday and Sunday.
- Two containers should be staged in the input queues of the loaders and the assembler.
- The output queues of the loaders should have a capacity of two.
- The system can achieve the desired throughput with the above specifications.

The company received several definite benefits as a result of the simulation study. First, they gained the assurance (before building the system) that the proposed design for the loaders, warehouse, and assembler would actually meet their

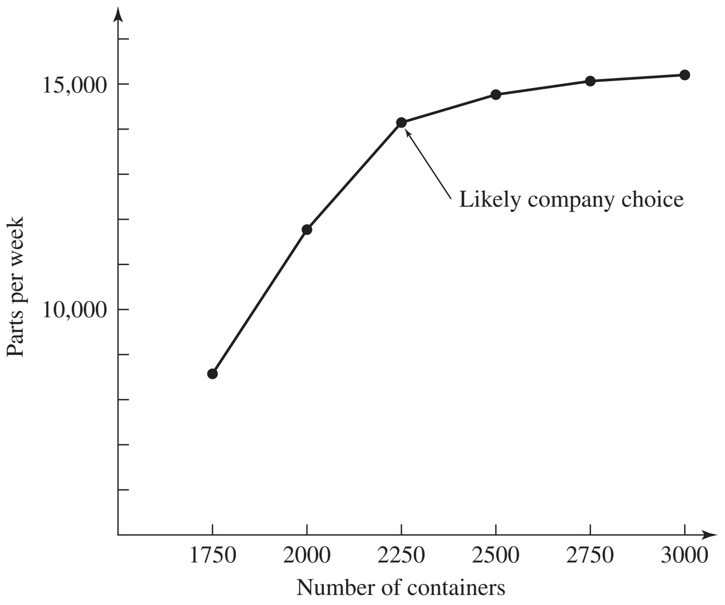


FIGURE 14.33
Throughput (parts per week) as a function of the number of containers.

specified throughput requirements. If a simulation study had not been performed and if a bottleneck were discovered after system installation, the cost of retrofitting the system could have been significant.

The company will probably buy 2250 containers rather than the 3000 originally in the budget, since the throughputs for scenarios 1, 8, 9, and 10 are all sufficient for the projected product demand. Since containers cost \$400 each, this is a savings of \$300,000. In addition, each container occupies 20.3 square feet of floor space, and the company expects to rent floor space at a cost of \$15 per square foot per year. Thus, by using 750 fewer containers, they will save \$228,375 a year in floor-space rental. Therefore, the total first-year savings are \$528,375.

PROBLEMS

14.1. For the system with no breakdowns in Example 14.3, show that the machine tool has sufficient processing capacity.

14.2. Consider a machine with uptimes $U_1, U_2, \ldots$ and downtimes $D_1, D_2, \ldots$ as described in Sec. 14.4.2. Is it *completely* correct to assume that the U_i's and the D_i's are each IID within themselves? Why or why not?

14.3. For the machine in Prob. 14.2, is it *completely* correct to assume that U_i and D_i are independent? Why or why not?

14.4. Consider a machine that operates continuously until a part jams; i.e., it is never starved or blocked. Suppose that a part has a probability p of jamming, independently of all other parts. What is the probability distribution of the number of parts produced before the first jam and what is its mean? Thus, if the average number of parts produced before a jam is known for an actual machine, the above model can be used to specify p for a simulation model.

14.5. Consider the calendar-time approach for modeling the up segments of a machine in Sec. 14.4.2. Suppose that a machine breaks down when it is starved. (Perhaps it was idling at the time.) Do you think that the breakdown would be discovered immediately (and repair begun) or when the next part actually arrives? Assume that availability of a repairman is not an issue.

14.6. Consider a machine that "operates" 24 hours a day for 7 days a week. The uptimes $U_1, U_2, \ldots$ and downtimes $D_1, D_2, \ldots$ are available, but not the corresponding busy times $B_1, B_2, \ldots$. Suppose, for simplicity, that an exponential distribution fits the U_i's. The average number of parts produced per 8-hour shift is known, as well as the average processing time for parts. Assuming that the exponential distribution is also a good model for the B_i's, what mean should be used for a machine-breakdown model based on busy time?

14.7. Consider a machine that is never starved or blocked. Suppose shop-floor personnel estimate that the machine has an efficiency $e = 0.9$ and typically fails twice in an 8-hour shift. What values of $E(U)$ and $E(D)$ should be used in modeling this machine?

14.8. Suppose that a machine will fail when either of two independent components fails. Describe how you would model breakdowns for the machine for each of the following two cases:
(*a*) The uptime of each machine is based on busy time.
(*b*) The uptime of each machine is based on calendar time.

14.9. Consider a machine that is never starved or blocked. It will fail when either component A or component B fails. These components fail independently of each other, and one component does not "age" while the other component is down. The mean busy time before failure and the mean repair (down) time for these components (in hours) are as follows:

Component	Mean busy time	Mean repair time
A	46.5	1.5
B	250.0	6.0

Compute the efficiency e of the machine.

14.10. Use a different method to compute the efficiency in Prob. 14.9 if busy time before failure and repair time are both exponentially distributed.

14.11. Consider a machine that has two types of failure. Type 1 is a minor problem, which is corrected by the machine operator with a "short" repair (down) time. A type 2 failure, on the other hand, is a major problem requiring a maintenance person and a "long" repair time. Suppose that n observations on repair times are available for the machine and n_i of them are of type i (where $i = 1, 2$), with $n_1 + n_2 = n$. Give two possible approaches for representing repair times in a simulation model. What are you implicitly assuming about the relationship between U_i and D_i (equal to R_i here)?

14.12. Simulate system design 3 in Sec. 14.5 with the change that an idle forklift has station 6 (input/output) as its home base. That is, an idle forklift will travel to station 6 to wait for its next job. Which of the two system designs is preferable?

14.13. For the manufacturing system in Sec. 14.5, why is the mean total service time averaged over all jobs equal to 0.77?

14.14. Using simulation, determine the required number of machines for each workstation and the required number of forklifts for the manufacturing system in Sec. 14.5 (original version) if each workstation has an infinite-capacity output queue. Thus, no blocking occurs.

14.15. For the manufacturing system in Sec. 14.5, why can the expected throughput not exceed 120 jobs per 8-hour day?

14.16. What is missing in Sec. 14.5 from the analytic calculations to determine the number of machines for each station? *Hint:* Can a machine always process a waiting part?

14.17. What is missing in Sec. 14.5 from the analytic calculations to determine the number of forklifts?

14.18. Why is the plot of Fig. 14.27 approximately linear? Give an expression for the slope.

14.19. What would you expect a moving average for system design 1's hourly throughputs (Sec. 14.5) to look like? See Fig. 14.30 for a similar type of plot.

14.20. For system design 2 (Sec. 14.5), why did the congestion level at station 5 get worse?

14.21. For system design 3 (Sec. 14.5), the proportion of forklifts moving loaded is 0.443 (to three decimal places). Thus, the average number of forklifts moving loaded is 0.886. Does this number look familiar?

14.22. Suppose for system design 3 (Sec. 14.5) that jobs arrive exactly 4 minutes apart. The arrival rate is still 15 per hour. Will the expected throughput be less than, equal to, or greater than 120? What will happen to the expected time in system?

14.23. For system design 3 (with exponential interarrival times), suppose that a job's service time is a constant equal to the mean service time in the original problem. For example, the service time of a type 1 job at station 3 is always 0.25 hour. How will the expected throughput and the expected time in system compare to the comparable performance measures for the original version of system design 3?

14.24. Perform a 2_{IV}^{6-2} fractional factorial design (see Sec. 12.3) for the manufacturing system of Sec. 14.5, using the following factors and levels:

Factor	−	+
Machines in station 1	4	5
Machines in station 2	2	3
Machines in station 3	5	6
Machines in station 4	3	4
Machines in station 5	2	3
Forklift trucks	2	3

The response of interest is the average time in system. For each of the 16 design points, make 10 replications of length 920 hours, with the first 120 hours of each replication being a warmup period; use common random numbers (see Sec. 11.2). Compute point estimates for the expected main effects and two-factor interaction effects. What are your conclusions?

14.25. Does the empty-containers stochastic process discussed in Sec. 14.6.5 have a steady-state distribution for scenario 7? Why or why not?