CHAPTER 1

Introduction

Business Processes and Simulation Analysis

A business process is a system of activities assembled to accomplish one or more of the goals of the business. These goals can be established using varying degrees of technical analysis, from simple intuition to a detailed study of a market sector. A strategy for meeting the established goals is usually defined, leading to the definition of products and methods for producing them. Simulation is a modern analytical technique that can be brought to bear at various stages of this development for the evaluation of alternative production strategies. In the past, such strategies have been compared by using index numbers such as Return On Investment (ROI), and other performance measures, based on static calculations. With available simulation techniques, however, process flows and activities under study can be allowed to fluctuate, yielding a detailed analysis of the costs and risks of human and material resources expended in production under uncertain conditions. Alternative business strategies for accomplishing defined goals can then be compared in relation to other process needs.

Business processes expose invested capital to risk. Approaches to risk, in a business setting, include acceptance, avoidance, management, or transfer. *Acceptance* of a risk generally leads to passing the costs of the corresponding loss along to the eventual customers. Thus the cost of rejected bad product, or other process loss, is often spread over the price of each good item sold. *Avoidance* of risk can take place through evaluation of process design alternatives, selecting the most productive or least risky. *Management* of risk can take place by adding costly safeguards to the process to prevent loss or mitigate its effects. In many such cases, simulation can assist the designer by evaluating the risks and the possible consequences of process changes before they are implemented. *Transfer* of risk typically occurs through insurance, wherein the insurance company charges a fee according to the expected loss. Proactive insurance companies also analyze the risk exposure and attempt to reduce it through recommended design or procedural changes. Risk reduction is one of the principal reasons for introducing simulation into business process analysis and design.

Every business process has uncertain elements and factors that contribute to risk. Examples might include the failure of production equipment, random lack of personnel, delayed arrival of entities to be processed, or the lack of timely availability of materiel used in the business. Loss can result from these random occurrences, and risk can be defined the degree of economic loss to be expected as a result of such uncertainties. The expected loss, E(loss) from all anticipated causes can be defined as the sum over these causes of the probability $p(e_i)$ of each loss event times the corresponding amount $C(e_i)$ that would be lost if the event were to occur. This is represented mathematically in Equation 1-1.

$$E(loss) = \sum_{i-1}^{N} p(e_i)C(e_i) \qquad (1\text{-}1)$$

It is evident that three means exist for loss reduction: (a) reduction in the number, N, of loss event types, (b) reduction of the probability of loss for each event, and (c) reduction in the consequential cost resulting from a loss event. Computer simulation is a tool that can be employed to reduce all three of these risk contributions.

Reasons for Simulation

Simulation is the study of a process through observation of the behavior of a model, over time, in response to a pattern of inputs. A model is a mathematical description of a process. The model variables behave like the variables in the real system, so we learn about the system by analogy, through observation of the model. An overview of this process is suggested in Figure 1.1. A model is subjected to a pattern of inputs similar to the pattern

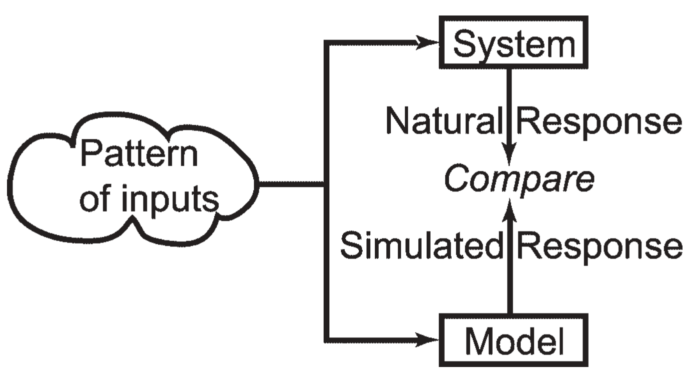

Figure 1.1 Overview of simulation development

experienced by the real system. Comparison of the natural and simulated responses validates the model, which can then be studied to uncover improved system designs. There are two broad categories of such systems and models, continuous and discrete. In a *continuous* system, variables representing states of the process can take on an infinite number of values, and changes between these values take place continuously. These values are generally expressed by real numbers, such as 25.4. To the extent that these systems are understood, their behavior can be mathematically described by ordinary differential equations, which express rates of change of the process variables. Mass flow and energy flow systems are typical of such systems, in which mass location and velocity (energy) are the stored states. These systems are simulated by repeatedly solving the corresponding differential equations, each such solution cycle generating a new state of the system. Variables in *discrete* systems, on the other hand, take on a countable number of integer values, such as the value 254, and these variables change instantaneously by discrete amounts. Such systems may be described by difference equations, which express incremental changes of process variables. Queuing systems, such as discrete manufacturing processes and service organizations are typical of these systems. In such systems, the lengths of the queues are states of the system. Note that the length of a queue increases instantaneously by one unit when a new customer arrives, and decreases by one unit when a customer is served. Simulation of these systems proceeds by generating model inputs in which the arrival times or numbers of simulated customers obey statistical distributions similar to the observed arrivals of real customers. Simulated entities generated according to these distributions are then entered into the model, where they are queued until they can be serviced. These entities (customers) are then withdrawn from this queue and are each processed for a statistically determined service time. The various effective rates and queue lengths of the simulated system are recorded during such a simulation, and inferences are subsequently drawn from these data about the behavior of the real system. The subject of this text will be the application of such simulations to the solution of the discrete systems that occur in business processes.

Complete mathematical solutions of process behavior over time may be difficult to obtain with many systems, and therefore computer simulation is often employed. Nonlinear behavior, in which output is not directly proportional to input, is typical of the difficulties such systems present. Because these systems are statistical, and the statistical distributions can also vary over time, and these discrete systems are called non-steady state. The changing frequency of telephone calls over the day would be an example of such a non-steady state system. There will be times with high calling rates and times with few calls per unit time. Different statistical models will be needed for these various conditions. Such systems, in which the system properties change over time, are also easier to study by simulation than by mathematical analysis. Other difficult problems to solve are those with very complex models and systems for which operations are poorly understood. The simulation of a large scale manufacturing process would be such a case. Computer simulation can help with the analysis of these complex systems because the number of variables that can be simultaneously considered in a computer model is very large. In the case of systems that are poorly understood, simulation using an approximate model can often exhibit behavior very like the actual system, so simulation offers some knowledge about even these poorly described systems.

There are a number of reasons, other than mathematical intractability, for simulating business systems. Simulation offers independence from the process, which would otherwise have to be understood by direct observation. Observing a process directly under all the various operating regimes of concern could sometimes be expensive or even dangerous. Simulation of the process of trading securities would be an example. It may be necessary to perform such simulations in order to train securities trading specialists, but conducting this training live, with real securities, would be far too costly. Processes that occur only once, or are inaccessible, are also candidates for simulation. Simulating the effects of a possible disaster on a hospital emergency room might be such a case. Simulation using an accurate process model can offer answers at negligible cost and risk in many of these situations.

Simulation can also offer a change of time scale. One or more years of business operations can be simulated in a matter of minutes. Simulating the path interferences that can occur with materials handling equipment in a busy warehouse could be considered as an example. Many months of warehouse operation can be simulated in a few minutes, rapidly detecting incidences of path interference. Conversely, human decisionmaking processes spanning minutes could be drawn out one step at a time by means of simulation, if an accurate model were known. The time scale of simulation is arbitrary, whether faster or slower than real-time.

Simulation is also frequently used as a design tool, either to explore design alternatives at negligible cost or to convince a sponsor that a design will work as projected. In this regard, it has become commonplace to supply a simulation model with proposed designs in certain industries, such as pharmaceutical manufacturing, where experimentation and iterative process improvement are not practical. A reading of the *Baseline® Guides* for engineering pharmaceutical facilities, for instance, would suggest applications of simulation to reduce processing delays in weighing, blending, coating, and handling of labile products. A recent case can serve as an example. This case involved a changeover from batch to continuous tablet coating that potentially could have produced significant holding area requirements for in-process materials under certain operating conditions. A process model was developed, and a simulation study based on this model was used to determine the required size of the holding area under various processing conditions. The results were then used to design the plant modifications for the proposed new process.

An extension of this idea is the use of simulation as a training tool. Flight simulators have been used in this role for many years in aeronautics. Dynamic simulation of discrete manufacturing and service processes, with behavioral variation or operator input, could be equally effective in training the operators of such business processes. In this application, simulation would reduce the time and cost of training an operator. It would also eliminate the off-spec product and risks to equipment that would otherwise occur during a live training cycle. As an extension of this notion, simulation could also be used to prepare operators for events not normally experienced, which could have costly consequences if they were to occur with an untrained operator. Application to the training of securities trading professionals has already been mentioned. Other examples might be supplied from the customer service and retail sales industries, where the objective would be to develop techniques for rapid and efficient handling of customers under varying conditions.

Simulation can also be used as a tool of inference in two ways. Firstly, a simulation model running in parallel with the actual process modeled could be used as a real-time diagnostic tool to highlight system faults of many kinds. This would presume the development of accurate models that remain valid under conditions of varying load. Secondly, a simulation, running after the fact with various hypothetical inputs and parameters, could be used to infer what might have gone wrong with a process and what might be done to fix it. Diagnostic and fault isolation methods of this kind could reduce the Mean Time To Repair (MTTR) of a system having a fixed Mean Time Between Failures (MTBF). This would increase its *Availability*, as expressed by Equation 1-2. The *Availability* of a system or subsystem is the fraction of total operating time during which the resource can be used. If greater Availability is needed, either the given resource must be made more reliable or alternative resources must be supplied during outages. Since the MTBF, on which Availability depends, is a function of the design of the resource, it is seldom under operational control. This means that higher Availability is to be obtained by process designs that include alternative pathways and redundancies.

$$Availability = \frac{MTBF}{MTBF + MTTR} \tag{1-2}$$

$$Unavailability = \frac{MTTR}{MTBF + MTTR} \tag{1-3}$$

The effects of outages can be simulated and such simulations used to reduce this risk component by engineering and management means. The *Unavailability*, given in Equation 1-3, is the fractional downtime of the system or subsystem, often due to a resource outage or lack of timely delivery of the entities to be processed. It is dominated by the Mean Time To Repair (MTTR), over which there is often operational control. Such outage time can be reduced by designing efficient flow of resources to a process, maintaining precautionary inventory levels of spare parts and raw materials, by rapid fault isolation and diagnosis, and by priority reallocation of labor or repair teams. Simulation studies can be used to improve the design of these support systems and operations. These many opportunities for simulation, coupled with the relatively low cost of high speed computing, make simulation an attractive option in the study of business systems.

The Process to be Simulated

Many business processes have been thoroughly studied in order to apply modern Materials & Resource Planning (MRP) techniques, and these studies can provide useful preliminary models for simulation study. The process to be studied through simulation is typically only one aspect or component of the whole system. Simulation of an entire manufacturing operation in detail would be a time consuming, and perhaps not very informative, exercise. Consequently, simulation study is usually restricted to a particular portion of the entire business. Simulation of only the warehouse operations of a large business, for instance, could produce understanding of just that small aspect of the larger manufacturing business, but it could possibly do so in enough detail to identify problematic delays. Simulation of an entire supply chain, a very large system, has been attempted, but such simulations would normally not be very detailed. A warehouse operation, in such a simulation, might be represented only by an approximate delay element. The behavior of individual machines for materials handling would probably be missing from such a simulation. Simulation scale is thus a matter to be resolved in any simulation study. In general, simulation detail is elaborated only far enough to adequately describe the activity of vital business interest.

A physical object or system, rather than a conceptual entity, is usually the subject of simulation. Due to its complexity, however, the behavior of such a system can not always be effectively described without statistical models. Even though a detailed physical model may be difficult to derive and mathematically intractable, these statistical models may represent average system behavior adequately for simulation purposes. The entities for which behavior is sought through simulation are discrete (countable), have times of arrival at some location in the process that can be measured. These entities wait in queues of countable length and are amenable to servicing or other processing requiring times that can be measured. These measurements will be important in building a statistical model of macroscopic behavior that can be used in a simulation study.

The Process Model

The behavior of the objects to be simulated will obey natural (physical or mathematical) laws, though these may be unknown. The exact behavior of people entering multiple queues in a supermarket may be unknown, for instance, but it is well known that customers awaiting service will divide themselves into as many queues as are made available. For a simulation study of customer checkout, then, a detailed model of human behavior may not be necessary, even if such were possible. A relatively simple model, such as minimization of waiting time, might suffice for simulation purposes. The level refinement of the model is the next issue to be addressed. That is, one must specify the degree of detail. In a manufacturing model, for example, operating divisions, process units, and unit operations would be successively finer levels of detail. Interviews with domain experts can be effective in defining the necessary degree of detail. At any level of model refinement, the simulated entities must be observable. Otherwise models of their behavior cannot be constructed and validated. We could not say much about the details of simulated warehouse operations, for instance, if we were only able to observe the number of raw material palettes or employees entering and leaving. For effective simulation, then, it must be possible to build an appropriately detailed model of the process to be simulated and to test this model against the behavior of the simulated system by imposing measurement conditions and observing behaviors.

The models of individual process operations are typically mathematical representations of that which is known about the process. As was stated previously, the mathematical representations in discrete system simulation are usually statistical in nature. Arrivals of customers and the times required to service them, for instance, are represented as statistical distributions. Many standard distributions are available to model the statistical behavior of business processes. Among these the Normal, Exponential, Poisson, Weibull and other distributions have been used successfully in many such models. The parameters of these distributions (mean value and standard deviation, for instance, in the case of the Normal distribution) are developed from direct observations. A statistical model is then matched to these data by adjusting the available parameters, and the resulting model can then be used in a simulation. It is not necessary to use such standard distributions, however, since special distributions can be developed to fit specific cases.

Business processes seldom consist of a single operation, so operational models must be linked together to form the overall model of the process to be simulated. That is to say, the overall process to be simulated can be divided into subprocesses, each of which can then be modeled. The subprocess models are then assembled into a system model in order to carry out the simulation. Computer packages for simulation incorporate this capability for introducing a hierarchic model structure. This greatly facilitates management of the inherent complexity of many business process models.

The Pattern of Inputs

Inputs to discrete processes take the form of entities, such as customers or units of product. These arrive at varying intervals, and in varying quantities. These intervals and quantities can be modeled as statistical distributions for purposes of simulation. The input entities also have *attributes* that can affect how they are handled by the process. Airline ticket class is such an attribute. Customers holding First Class tickets are processed differently from customers holding Economy Class tickets, for example. First Class ticket holders enter a different queue from Economy Class ticket holders and are expeditiously served by highly qualified attendants. Thus both shorter queue length and shorter service time may be experienced. Other attributes can affect eventual processing time. A customer who shops weekly for a family of six requires more checkout time at the supermarket than one who only buys a few items, perhaps on several visits each week. In this case, the number of items in the shopping basket is the significant parameter. An analogous example would be the size of a data frame to be processed in a data communication network. The length of the frame would affect the processing time. Thus times of arrival, eventual processing times, and attributes affecting handling are important parameters to enter into a simulation model.

The System Response

The direct response of a discrete process, or queuing system, is the length of the queue at the input to a process operation. This changes with each incoming entity and with each entity drawn from the queue for servicing. Incoming entities go into the queue, increasing its length; entities entering service are withdrawn from the queue, decreasing its length. In effect, the queue is where the operation puts incoming entities awaiting service. The queue expands and contracts in response to inputs and services rendered, the number of entities waiting in the queue being a *state* of the system.

The service time is an indirect response to input. It can be affected by an attribute of the input and the quality or type of service, not the arrival of the input. The service to be performed will also require resources, and service times will be affected by the availability of such resources. Service times may be statistical or predetermined, but are always part of the operational model in a discrete process simulation.

The Observations for Building a Model

Models of processes to be simulated are generated by observations of an operating process or operation. Inputs, the arrivals of entities to be processed by the system, are recorded. Times of arrival and the values of any attributes that might affect processing time are recorded for a large number of samples. The arrival times of airline customers and their classes of tickets would be an example. If possible, the number of entities awaiting service in each queue may also be recorded, although this is redundant information. In the airline example, the number of airline customers in each line could be recorded. Processing times in each operation of the process would also be recorded. In the example, this would be the time required for each airline customer to check in. Outputs, entities leaving the process, would also be recorded. For the airline example, these would be customers checked in, placed on standby, or rejected. It should be noted that, in some cases, these entities could be different from the entities entering the process. This would occur in a manufacturing operation, for instance, where a number of input components are combined into a single output product entity. It should also be noted if entities leave a queue without being served. When all these data have been gathered, models may be built that describe the statistical properties of the process and its inputs.

Validation of the Model

A simulation model is based upon a mathematical representation of the actual process or operation to a certain degree of detail. As such a generalization, it may exoected to be inaccurate or incomplete, since is is necessarily a simplification. The testing of the adequacy of a model and its comparison with actual operations is called *validation*. A model must be validated before it is used in simulation. More will be said about this step in discussion to follow, but essentially the model must produce the same data as the process, when subjected to the same sequence of inputs. Arrivals of inputs, queue lengths, lengths of time at process units, and times of exit will be recorded and compared with those predicted by the model. It is best to perform this step with *new* data, rather than the data used to develop the model. This will prevent the model from only representing one set of data. Once the model has been validated as accurate and independent of the data set, simulation study can proceed.

Designing the Simulation Study

A simulation study will be designed with a particular objective, be it the capture of process know-how, the evaluation of alternative operating regimes, the selection of optimal operating parameters, or the calculation of operating costs in relation to resources used and activities performed. The model developed must be adequate to these tasks. If operating parameters and regimes are to be evaluated, then large quantities of data must be gathered in order to develop accurate statistical models. If costs are to be estimated, then cost models must be thoroughly developed. Such goals should be clearly defined. Suitable data should be collected, models should be validated, and appropriate simulation experiments should be designed to accomplish these goals.

An Example: Manufacture of Electronic Instruments

Problem statement:

An electronic measuring instrument is to be manufactured in response to orders. Orders arriving with a Normally distributed Mean of 4 weeks and Standard Deviation of 1 week, will be batched in each manufacturing cycle, with the number of cycles per year depending upon the volume of orders. Each cycle will consist of the following components:

(1) Batching of Orders
Orders occurring over two months (8 weeks) are combined into batches of up to 4 orders. These determine the total number of instruments to be manufactured in a production cycle. Multiple items of product may be contained in a single order, so order size is a significant parameter.

(2) Purchasing of Components
A parts "explosion" is produced for each order, and similar parts are coalesced by type and vendor. Purchase orders are issued. Received components are inspected and placed in inventory until all orders have been completed. Extra parts are ordered to offset manufacturing losses and for economy of pricing. The whole purchasing process takes a Normally distributed time with a Mean of 8 weeks, and this time has a Standard Deviation of 2 weeks.

(3) Assembly of Products
Components are assembled into products and prepared for testing. Assembly depletes the inventory of ordered components. Only one assembly line is available, so two batches cannot be processed simultaneously. Assembly time is Normally distributed, with a Mean of 1 week and a Standard Deviation of 1 week.

(4) Testing of Products
Assembled products are "burned in," tested, and calibrated before shipment. Products failing test are rejected, held for rework, reworked, and then held for spare parts or demonstration uses. Products are individually tested, and only four (4) can be

tested simultaneously. Testing requires a Normally distributed Mean of 1.5 weeks, and this time has a Standard Deviation of 1 week.

(5) Shipping of Orders
Orders are packed for shipment, packing lists are printed, and orders are shipped. Orders are shipped sequentially. Time needed for shipping is Exponentially distributed, with a Mean of 1.5 weeks.

Goal of the Simulation:

Simulation is to be used to determine the delivery schedule, which will be quoted to customers. Bottlenecks and risks are to be identified, for possible risk reduction through expansion of capacity and lead time reduction.

Procedure:

A block diagram of the process is drawn. This is shown in Figure 1.2. Each rectangular block represents a process operation leading to the finished product. Special blocks are used to indicate the source of orders and the final customers. Between process blocks, the input/output entities are named. In a simulation, the orders would be generated according to a statistical distribution that would approximate the observed arrival of orders. The block diagram represents a simulation model of the production process. It is an overview. Detailed models for each block will be developed by observing the process in operation and gathering statistical data. Statistical distributions are then developed for the gathered data and are entered into the process model. The corresponding model will be validated by comparison with past operating data. A simulation run will then be conducted. This might show, for instance, that an order takes between 10 and 25 weeks to complete. The company could then safely quote its delivery time at 6 months (26 weeks) after receipt of order. If this is too long, or the dispersion of completion times is too great, the simulation can be studied to ascertain which operations can be improved.

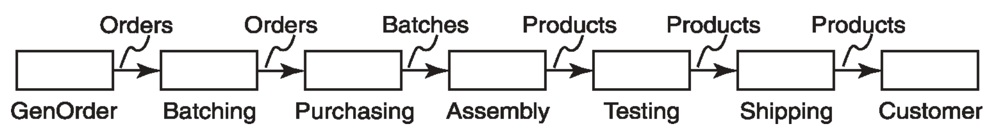

Figure 1.2 Block diagram of instrument manufacturing process

Risk Analysis

There is risk of a late delivery penalty of 10%, an average of about $2000 per order, for any order delivered later than the promised delivery date. Figure 1.3 shows the simulated delivery cycle times for 130 typical orders. Although some fluctuation of these results is to be expected with simulations using different random number streams, the graph shows that penalty payments can be expected on 3 of the 130 orders, for a delivery time set at 26 weeks. If the delivery were set at 24 weeks, on the other hand, 14 such penalties could be expected.

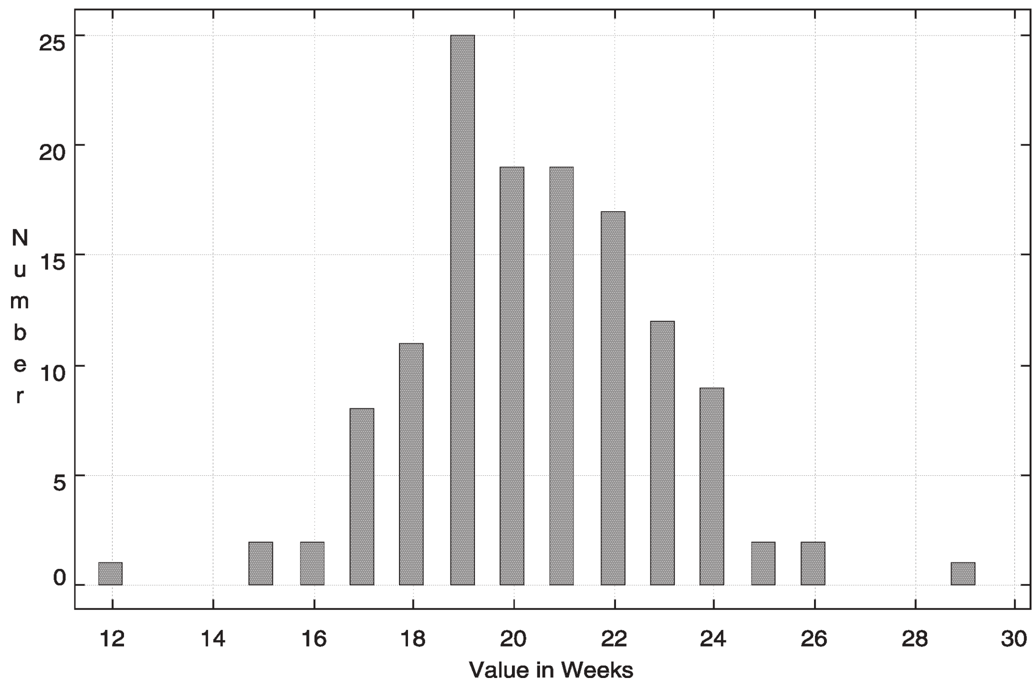

Figure 1.3 Simulated order cycle times for instrument manufacturing example

Two strategies for dealing with the risk suggest themselves:

1. Risk Acceptance
   The risk of 3 payments will be accepted and penalties will be paid as incurred. Greater risk, by quoting earlier delivery, will not be accepted.

2. Risk Management
   A portion of the expected risk payment will be used to reduce the number of penalties incurred, by early component purchases or extra labor. This is expected to eliminate 1/3 to 1/2 of the late delivery penalties.

Simulation has thus provided not only a risk estimate but has also produced a bound on the amount that can reasonably be spend on risk avoidance.

Summary

Reasons for simulation include mathematical intractability, the need for independence from a process, change of time scale, and possible utility in design, training, diagnostic inference and risk estimation. The simulation procedure requires observations on an operating business, construction of a process model, validation of the model, generation of input data according to a statistical distribution, recording the behavior of the simulated process in response to those inputs, and analysis of the results for possible modification of the process to improve operations or reduce risk.

Review Questions

(1) Name a number of continuous systems.

(2) Name a number of discrete systems.

(3) Name some reasons why an airline ticketing system would be a good candidate for simulation. Describe some problems that could occur in such a simulation attempt.

(4) Name some reasons why a car wash would be a good candidate for simulation. Describe some problems that could occur in such a simulation attempt.

(5) Name some reasons why an automated warehouse would be a good candidate for simulation. Describe some problems that could occur in such a simulation attempt.

(6) Name some reasons why a purchasing system would be a good candidate for simulation. Describe some problems that could occur in such a simulation attempt.

(7) Name some reasons why a customer service system would be a good candidate for simulation. Describe some problems that could occur in such a simulation attempt.

(8) Describe would the design of an automobile suspension system would probably not benefit from discrete system simulation, while the design of the production line might be an excellent candidate.

(9) Describe why the control of catalytic cracking in a refinery might benefit from continuous system simulation, but the off-loading of container ship could probably benefit from discrete system simulation.

(10) If you were to design a production system for making and packaging cookies, would you use continuous or discrete system simulation to study process alternatives?

(11) Describe why discrete system simulation might be a good candidate for evaluating alternatives in the design of a stock market trading system.

Design Homework

For the suggested design problems below, please draw a block diagram of the operations to be simulated indicating the various items (entities) moving through the process and the operations performed. Please take note of any places in which material in process might accumulate in a queue, whether as individual units or in batches. Please take note any expected risks and describe how these could be managed.

(1-1) Design a hypothetical plant for manufacturing and packaging cookies.

(1-2) Design a hypothetical plant for manufacturing bicycles.

(1-3) Design a model for a shoe repair business.

(1-4) Design a model for a warehouse operation.

(1-5) Design a hypothetical customer service organization.

(1-6) Design a hypothetical Web shopping business.

(1-7) Design a process for issuing new driver's licenses.

(1-8) Design a chat room system for hosting a virtual open house.

(1-9) Design a model for a car wash.