

# 4 Starting a Simulation the Right Way

A computer simulation project is more than purchasing modeling software, plugging in a few values and expecting an answer to a question to pop out. This chapter considers the broader picture that simulation encompasses by developing a methodology for starting the process correctly. However, before that is discussed, a failed project is examined.

## Case Study: The Wrong Way

A young engineer, fresh out of college and ready to take on whatever challenges her new job had to offer, was assigned the task of simulating a proposed materials handling system. The system would be installed in a large engine plant having thirty manual assembly stations. Engine blocks would enter the system and be moved from station to station via automated guided vehicle (AGV). At each assembly station, an AGV would drop off the engine block together with a part tray. The station operator would perform the required work then press a button to signal for engine removal. An available AGV would be dispatched to the station and the engine would move to its next stop in the assembly operation. The concept seemed to be workable in theory, so a simulation was initiated to validate the concept.

This was one of the first simulations the young engineer had developed and so she was careful to use a text book approach to the project. She was given an objective by the senior system engineer of 'see if it works'. The next step was to gather information about the system. She obtained work cycle times, a plant floor layout, information about the factory breaks and lunches, shift information, AGV speeds, AGV loading and unloading times, system priorities, and other operational data. Feeling confident this data was adequate, she commended coding the model.

Model development was more complicated than the young engineer had anticipated. By the time the simulation was written, its scheduled completion time had all but elapsed. The initial run of the system demonstrated the required number of engines could not be manufactured. Tempers flared under the tight time constraints and the simulation was given a new objective of 'making it work'.

Feeling pressured, she (with the help of a seasoned analyst) identified thirty-two controllable factors in the model. These were altered and tried in different combinations but desired throughput could not be obtained. Finally, a solution was found but it would require assembly workers to operate at inhumanly fast speeds at certain stations. Management at the engine plant felt no more time extensions could be granted and the system was installed.

For the first year, the system was slated to operate at half capacity. When the time arrived to ramp up to full operation, as the engineer had determined earlier in the simulation, the system was unable to meet required throughput. The simulation was brought out for further review but it only confirmed the real-world situation. The model was updated and different ideas were tried. Eventually, a costly solution was implemented by adding automation hardware to parts of the system.

Simulations can go terribly wrong, particularly if the appropriate infrastructure is not carefully developed to support the modeling effort. Few simulation analysts can report that all of their models are flawless. The previous example analyzed a real simulation project that became disastrous and the steps taken to revive it. Although the model had been accurate, the simulation received criticism and blame for the problems. Several pitfalls can be identified by looking at the process in retrospect.

- First: The simulation analyst was inexperienced. She lacked practical knowledge of the system's operation and this slowed initial model development.
- Second: The simulation 'team' members didn't participate adequately. Although the model demonstrated problems did exist, time was not taken to solve these problems as a preventative measure. Rather, the system was installed and then problems were tackled at a much higher cost.
- Third: Goals changed mid-simulation effort. The original simulation was meant to discover if the would work. When production fell short, a new goal of 'making it work' became the directive.

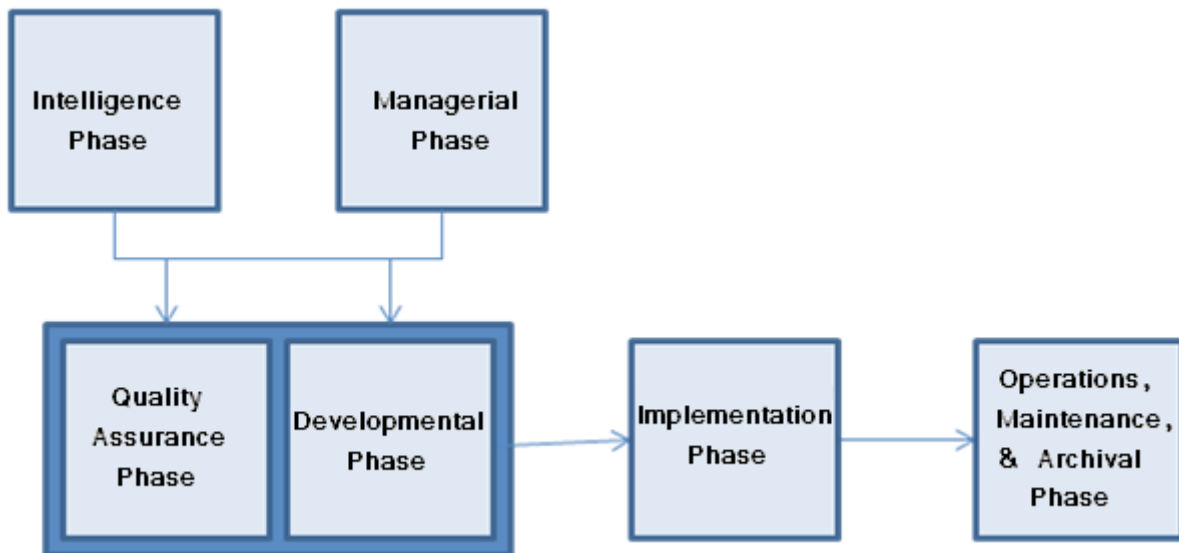
The problems pointed out by this case study could have been avoided if the simulation effort had been taken more seriously. If preventative action had addressed system inadequacies early, costly corrections and time delays could have been avoided.

A recent study of discrete event computer simulation projects revealed unsuccessful efforts are characterized by high costs, model size constraints, and slow software. In contrast, successful projects are characterized by teamwork, cooperation, mentoring, effective communication of outputs, high-quality vendor documentation, easily understood software syntax, higher levels of analyst experience, and structured approaches to model development. While these findings should not come as a surprise, the importance of having a structured methodology for approaching a simulation is apparent. The next sections of this textbook provide a detailed view of an approach to help enable simulation project success. The process used in this textbook is representative of many possible computer simulation project life cycles that have been used in practice and documented in simulation textbooks and journal articles.

However, remember each simulation project is unique and specific requirements may be better served through customizing the steps discussed. In general, the simulation project life cycle described in this book consists of six major steps, each having multiple components. The major steps being investigated are:

1. **Intelligence Phase.** The precursor to any solution is full development and an understanding of the underlying dilemma or problem.
2. **Managerial Phase.** In general, this step requires interaction with management and other non-technical staff of the organization to acquire necessary resources and support along with the formation of a simulation project team.

3. **Developmental Phase.** During this phase, the simulation model or models are created. System design, detail design, and coding all take place and rely on the interaction of the analysts and other members of the simulation team.
4. **Quality Assurance Phase.** While the model is being coded in complete or at least in prototype form, the analyst must ensure proper validation and verification. The ideas of testing and completion or integration are also important here. It may be necessary take testing one step further and begin development of face validity through interaction with end-users and management. Generally, quality assurance accompanies the entire modeling lifecycle.
5. **Implementation Phase.** Model use begins and decision support activities take place.
6. **Operations, Maintenance, and Archival Phase.** Development is essentially complete and only maintenance tasks remain. This phase may be substantial if the project results in a simulation maintained for repeated use



**Figure 4.1** General Simulation Lifecycle

A simulation project can be a complex organizational undertaking. In general, to believe a simulation project starts and ends with coding a model would be a mistake. Much more is involved. In many instances, modeling is one small component in a much larger simulation project life cycle. As stated previously, a simulation project is inclusive of a wide spectrum of activities ranging from system and problem definition to ensuring logic developed in the model can bridge the gap between model and real world and be used in actual system implementation. The following sections provide a closer look at the mechanics of conducting a professional simulation study.

## 4.1 Intelligence

The intelligence phase of the simulation life cycle involves understanding the environment and determining problems to be solved. In general, this phase consists of the simulation analyst or potential simulation customer discovering situations that require modeling. The simulation analyst should emerge from this phase with knowledge that a problem exists and should have at least a preliminary understanding of the problem's nature. Often, problem definition and feasibility are assessed at this point in time.

### 4.1.1 Problem Definition

In order to ensure simulation project success, several events need to occur before any other work begins. First, the customer needs to define objectives for the study. The objectives for the simulation describe what questions the simulation needs to answer. In other words, the precursor to any solution is a full understanding of the underlying dilemma or problem. Parameters for the problem as well as broad scale constraints need to be defined. A simulation project may be driven by a broad statement such as "The Denver Chamber of Commerce has projected that incoming passenger flights will increase by 50% over the next 18 months." Definition of the problem operationalizes the statement and looks at the system environment to clarify goals for analysis.

For example the problem definition may become:

Can the existing baggage handling system handle the project increase in passenger arrivals and departures?

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Of course, this question could rapidly be replaced with a related:

What needs to be changed in order to accommodate the expected increase in passenger arrivals and departures?

These sorts of clarifications need to be made early in the simulation life cycle.

#### 4.1.2 General Feasibility

Together with problem definition, it is common to conduct a preliminary feasibility study at this point in the simulation life cycle. The feasibility study may be focused on various characteristics of the project and may seek to answer questions such as:

Will a model provide an answer to the question?
Can an accurate model be developed?
Can model development be accomplished within the desired timeframe?

**Table 4.1** Feasibility Questions

As with any general simulation software development effort, feasibility may be assessed in a variety of areas. One model for feasibility is TELOS which stands for appraising technical, economic, legal, operational, and schedule feasibility.

## 4.2 Managerial Phase

A means for gathering information needs to be established. This requires obtaining support from management, domain experts, system users, and other individuals in order to understand and document the system that will be modeled. In other words, simulation requires teamwork and in most cases cannot be done by a lone individual.

The managerial phase facilitates organizational involvement in a simulation project. A number of overhead tasks are accomplished here including development of proposals, securing a budget, acquiring managerial support and forming a project team. Often, the development of a simulation proposal is used to organize effort and ensure all participants are working toward a common goal.

A project kick off meeting might be held at this point in time and expectations of higher level management might be discussed to avoid situations where the modeling effort degrades into a prolonged search for potential solutions to poorly defined problems.

### 4.3 Developmental Phase

After the objectives for a simulation study have been stated and resources allocated, modeling can begin in earnest. In general, modeling involves developing a representation of the system. A working definition for a system is:

A set of components or elements that are related to each other in such a manner as to create a connected whole.

The relationships between elements comprising the system are essential in predicting the behavior of the whole. If the system is reduced to a group of independent subsystems, each can be studied separately, but the true characteristics of the system may be lost. It is critical to maintain interaction between various system elements.

The orchestra shown in Figure 4.2 provides an example of a system with complex interacting elements.

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**Figure 4.2** Chicago Symphony Orchestra

Various subsystems consisting of groups of musicians playing similar instruments are related to each other in such a way as to create a connected whole. The stringed instruments can be viewed as a subsystem. So can the musicians playing only the first violin part. Percussion, brass, clarinets, flutes, cellos, French horns, and oboes can all be defined as subsystems. The various groups of musicians are dependent on their musical score and the direction of a conductor to achieve an overall goal. Each subsystem can be removed from the system, studied and analyzed, but it would become very difficult, if not impossible, to predict the overall behavior of the system in this way.

A system can be broken into its individual elements structurally. However, it cannot be broken into individual elements and still maintain its functionality. For example, a computer system can be studied in terms of its components such as microchips, wires, capacitors, resistors, transistors and electricity. If such a study was completed, the true characteristics of a computer would be lost. The crucial interaction between the individual components would not be present.

Within the context of a simulation project, the importance of viewing the system as a whole is quite evident. In order to maintain an accurate representation all interactions between the various components must be included in the model. In addition, the components and their interrelationships, the system's environment and boundaries need definition (Figure 4.3).

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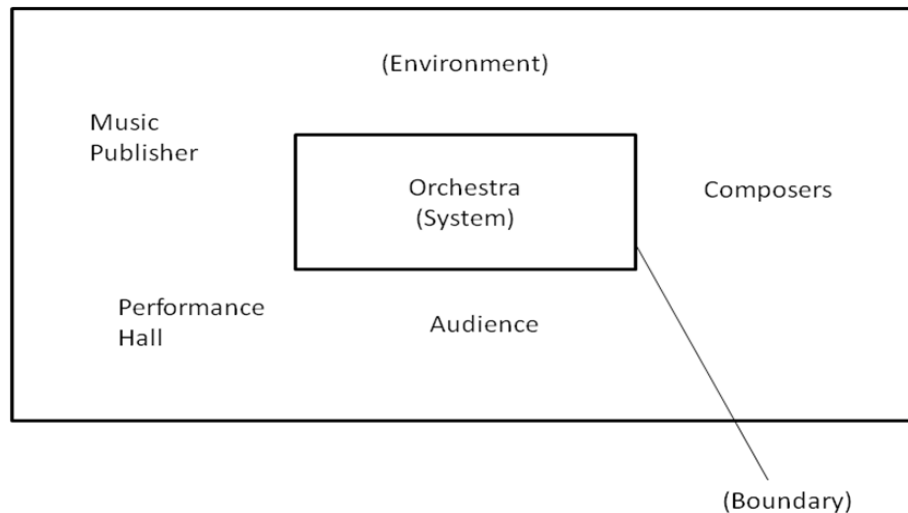
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**Figure 4.3** Environment and Boundary

The environment lies outside the system and has influence on its behavior but is not controlled by it in any way. A system's boundary is the line that separates a system from its environment. In the development of a simulation, influences of the environment must be taken into consideration and can be represented with constraints, rules, and events.

Environment and boundary can be illustrated using the example of an assembly line in a United Auto Workers (UAW) unionized plant. The system to be modeled is an auto assembly line. The system boundary encloses the materials handling system, the assembly operation, the assembly operators, and the product moving through the system. The environment which exerts influence on the system would be the set of union rules for coffee break times, the lunch break, shift change and holidays. The influence of these environmental factors can be represented in the model with various operational rules and events that impact model outcomes.

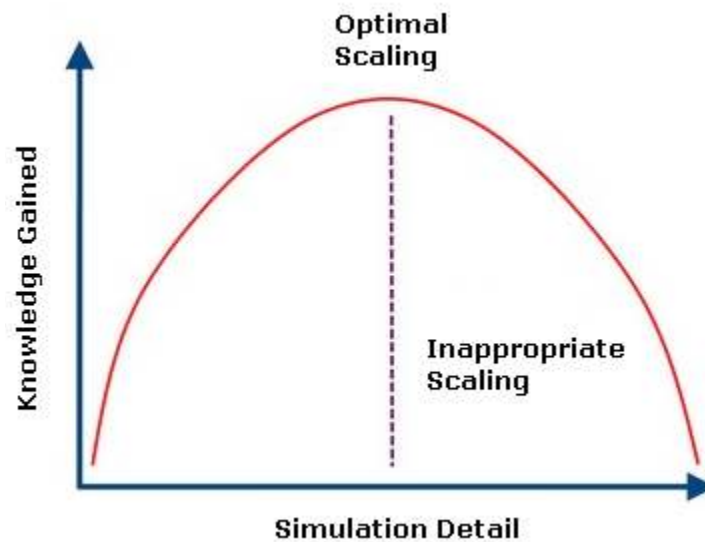
The division between system and environment is often a very delicate line to try to define. The aptitude for defining systems, subsystems, and environment is an acquired skill that might take years to refine.

In general, during the development phase the simulation model is created. System design, detail design, and coding all take place and rely on the interaction of the analysts and other members of the simulation team. A number of considerations must be included during model development.



### 4.3.1 Model Scaling

Model scaling is a determination of how much detail is required to emulate the real world system and still accurately provide the required information. Since a model is an approximation of a real world system under study, it is not always best to develop a full scale representation. If the system were modeled down to the finest detail, excessive time and energy would be expended with minimal gain in useful information. The law of diminishing returns can be applied to level of detail versus gain in knowledge. See Figure 4.4.



**Figure 4.4** Scaling vs. Knowledge Gained

A recommended approach to model development is to incorporate the least amount of detail while still maintaining veracity of the simulation. This process, called scaling, is a subjective skill developed as a simulation analyst becomes more experienced. Different analysts will build their models with varying levels of detail with an ultimate goal of creating a valid and useful simulation.

#### Computer Manufacturing Company: Serial Partitioning of a Model

A manufacturer of microcomputers needs to develop a model of its manufacturing and shipping operations. The analyst assigned to the project decides a single model would be too complex to develop with current time constraints and decides to focus on key portions of the system using serial partitioning. The first step in using this technique is to identify a natural break in the system's operation. After collecting data he finds all manufactured computers are stored in a warehouse and when ordered by a customer, are removed and proceed through the packaging and shipping operations. The point at which the computers leave manufacturing and enter the warehouse is a natural break. The interaction is one way and could be used as a place to break the model into two separate serial portions. The outputs from the manufacturing model will be used as inputs to a future storage and shipping model.

### 4.3.1 Model Scope

As part of system definition, model scope must be determined. Model scope determines the portion of the system to be represented by the model. Partitioning is a common technique used to do this and to help keep a model's size manageable. Partitioning involves studying individual subsystems and determining which can be represented by a single construct and which need to be modeled in more detail. This technique can work very well under certain circumstances, particularly when little interaction or interdependency occurs between the subsystems, caution should be exercised to avoid oversimplification.

Partitioning can be either serial or parallel. Serial partitioning will break a system into separate successive stages for modeling. The outputs from each stage will become the inputs for the next stage. If the interaction between the stages is unidirectional, serial partitioning may be adequate. If the interaction is bidirectional and complex, with a complex interdependency between the systems, partitioning should not be used. As an example, consider the following case:

Parallel partitioning can be used where a set of independent, identical processes are replicated a number of times. These processes can be modeled by a single entity having the capacity to simultaneously perform duties that in reality would occur in parallel.



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Defining which parts of the system need to be modeled is very important to the success of a simulation project. Modeling in too much detail leads to excessive development time and unnecessary complication. Too little detail may result in a model which does not realistically predict actual world behavior. The analyst must use caution during this part of the simulation process to insure the model accurately reflects system operation.

#### 4.3.2 Modeling Views

Development of a simulation requires a system be viewed in a manner that will facilitate the modeling process. Nearly all available simulation software products use one of three approaches: event orientation, process orientation or activity orientation. And, of course, use of a particular modeling tool or language may make this decision for the analyst by default.

Event Orientation – Using this modeling approach requires the simulation analyst to identify all events that might occur and determine the impact these events will have on the system. An event is defined as any instantaneous occurrence which may change the state of a system. The following example illustrates an event orientation approach used in defining a system.

##### K-State Credit Union Drive-through Bank Teller: A Second Look

After contemplating the use of the event orientation approach, Ms. Ida decided she would be better served to model the drive-through using the process orientation approach. After some research and careful thought, she developed the diagram shown in Figure 4.5. A customer entering the drive-through lane is considered to be a transaction and the teller, a permanent resource. The process routine describes the experience of the customer from the time he or she attempts to enter the lane until the time he or she completes interaction with the teller. Time passes while the teller performs the desired service. Time may also pass while the customer waits in queue for the teller resource to become available.

Process Orientation – A process is a time ordered sequence of interrelated events separated by passages of time. This sequence will describe the entire experience of a transaction as it moves through a system. When the process orientation approach is used, the modeler will define repeatable sequences of steps each representing an event or a series of events. These sequences of steps can be represented by a network or flow diagram. Objects, which may be required by a transaction during its movement through the sequence of steps, are defined as a resource. The following process orientation example takes another look at the K-State Credit Union drive-through.

### K-State Credit Union Drive-through Bank Teller

Keri Ida, manager of the new K-State Credit Union branch opening near campus has to determine the number of tellers for the new drive-through service lanes. She thinks one or two tellers would be best and decides to develop an event oriented model to help make the determination. Ms. Ida identified the following key system events:

1. Customer Arrival - If the teller is occupied, then the person arriving will wait in queue. Otherwise, the person uses the services of the teller.
2. Customer Service Complete - Following completion of service by the teller, the customer leaves. The next person in queue can be serviced. If the queue is empty, the teller becomes idle.

Ms. Ida knew if either one of these events occur, the system's state would change. Having identified the key events, she was ready to begin coding his model using the event orientation approach.

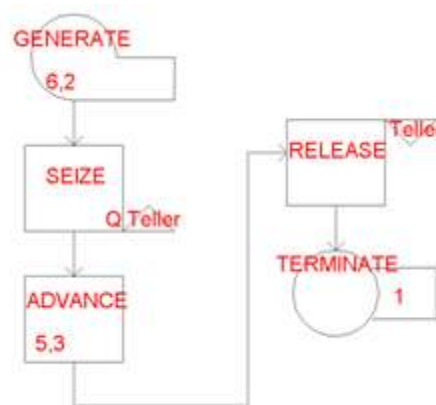


Figure 4.5 Block Diagram for Bank Model

Activity Orientation – The activity orientation approach is less commonly used. It involves describing a system in terms of the conditions necessary to either start or stop an activity. The beginning or conclusion of an activity will have an effect on the system state. Activities may require specified amounts of time for completion or may be brought to completion by meeting certain logical conditions.

### 4.3.3 Concept Model

Another early activity often utilized in a simulation project is the development of a general concept model. A concept or rough-cut model is a general model which can quickly produce an approximation of a system. Concept modeling is used to provide answers in the initial stages of a simulation indicating whether time and resources should be invested in a more detailed model. These rough-cut models can take the form of anything from a simple mathematical equation done by hand to a sophisticated network analysis done on a computer using specialized modeling software. Spreadsheet software is often the tool of choice for a concept model.

A great deal of work and effort in a simulation project often can be saved by taking a final look at system components from a quantitative viewpoint. If certain operations are mathematically infeasible, it may be desirable to postpone the detailed simulation and re-evaluate system design or even the premise of the project. The following example illustrates the use of simple mathematics to avoid an unnecessary simulation (See PikNGo: First Concept Model).

#### PikNGo: First Concept Model: Rough Calculations

PikNGo Packing and Storage uses a fleet of twelve forklift trucks to transport pallets of material to and from storage locations in their vast warehouse facility. Recently with labor disputes and higher fuel costs, upper management has decided to consider replacing the aging forklift fleet with an automated guided vehicle (AGV) system. To help provide a preliminary estimate of the costs involved, PikNGo performed a rough set of calculations. Although a more detailed simulation is desired, the concept model was intended to indicate whether a more detailed simulation should be considered. Management had already looked at a budget and believed no more than a ten vehicle system could be afforded. Table 4.2 illustrates.

#### Results of Rough Calculations

Initially, the following numbers were used:  
 Number of Loads Moved Per Day: NLD: To Be Determined  
 Average Time to Move a Load: ATM: 12 Minutes  
 Number of AGVs: AGV: No More than 10

$$\text{TLPH} = \text{Total Loads per Hour} = (60 \text{ minutes} / \text{ATM}) * \text{AGV}$$

$$\text{TLPH} = 60 \text{ Min} / 12 \text{ Min} * 10 \text{ AGV}$$

$$\text{TLPH} = 50 \text{ Loads}$$

**Table 4.2** Rough Calculations for PikNGo

**PikNGo: Second Concept Model: Queuing Model with Spreadsheet**

Currently PikNGo moves an average of 75 loads per hour so the rough calculations demonstrate the system falls short of the desired throughput. However, the model is not detailed and so rather than end here management decided to continue the analysis with more detail, this time using a spreadsheet queuing analysis model. The results shown in Table 4.3 were obtained. The numbers verify that only 50 loads could be moved in the desired time. A further run of the model indicated

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Queue Station	AGV_Queue	
Arrival Rate	75	Number of Loads to be Moved per Hour
Service Rate/Channel	5	Number of Loads an AGV can Move per Hour
Number of Servers	10	Number of AGVs Available to Move Loads
Max. Number in System	***	
Number in Population	***	
Type	M/M/10	
Mean Number at Station	#NUM!	
Mean Time at Station	#NUM!	
Mean Number in Queue	***	
Mean Time in Queue	***	
Mean Number in Service	10	
Mean Time in Service	0.200000003	
Throughput Rate	50	
Efficiency	***	
Probability All Servers Idle	***	
Prob. All Servers Busy	1	
Prob. System Full	***	

**Table 4.3** Spreadsheet Showing 50 Loads Moved with 10 AGVs

Queue Station	AGV_Queue	
Arrival Rate	75	Number of Loads to be Moved per Hour
Service Rate/Channel	5	Number of Loads an AGV can Move per Hour
Number of Servers	16	Number of AGVs Available to Move Loads
Max. Number in System	***	
Number in Population	***	
Type	M/M/16	
Mean Number at Station	25.95113945	
Mean Time at Station	0.346015215	
Mean Number in Queue	10.95113933	
Mean Time in Queue	0.146015191	
Mean Number in Service	15	
Mean Time in Service	0.200000003	
Throughput Rate	75	
Efficiency	0.9375	
Probability All Servers Idle	1.45347E-07	
Prob. All Servers Busy	0.730075955	

**Table 4.4** Spreadsheet Showing 16 AGVs required to Move 75 Loads

Using a rough-cut or concept model prior to building a detailed simulation can provide the analyst with several benefits. These include:

1. Help identify problem areas early in the project.
2. Reduces the time and cost associated with unnecessary detailed simulation.
3. Allows rapid “what-if” testing.
4. Easy to use, inexpensive, and widely available. Spreadsheet software can be used in many instances.

#### 4.3.4 Concept Modeling with Simple Spreadsheets

A simple spreadsheet can be used to rapidly prototype a model and to provide a general sense regarding a system’s scope. This approach has advantages including speed of development but, if not used carefully and with a sense of its preliminary nature, can result in false expectations. The following example provides a simple spreadsheet example of concept modeling:

##### FastWay Delivery

FastWay Delivery Company decided to open a new branch office that would deliver bread and bakery items to grocery stores and service stations in its immediate area. Ten different routes were mapped out, each one consisting of varying distances and numbers of stops. An average speed in miles per hour was calculated for each route based on expected traffic congestion and legal speed limits. FastWay wanted an approximation of the number of delivery vans their new operation would require. They developed a concept model using Google Spreadsheet and these assumptions:

##### Assumptions

- 1) A route is a round trip leaving the bakery, servicing all stops, and returning to the point of origin.
- 2) A route can be taken at any time during the eight hour work day.
- 3) If a delivery van finishes its route before the work day is over, it will start the next route.

The spreadsheet that was developed is shown in Figure 4.6.



Route #	Distance (Miles)	Average Speed (MPH)	Number Stops	Average Time per Stop (Min)	Total Trip Time (Min)
1	15	17	4	10	92.94
2	12	15	4	10	88.00
3	13	15	4	10	92.00
4	18	20	6	10	114.00
5	24	25	8	10	137.60
6	52	25	8	10	204.80
7	28	20	6	10	144.00
8	29	30	6	10	118.00
9	58	40	10	10	187.00
10	61	40	9	10	181.50
<b>Totals or Averages</b>	310	24.70	65	10	1,359.84
<b>Over 8 Hours</b>	2.83	<b>Delivery Vans Required</b>			

Figure 4.6 FastWay Spreadsheet

FastWay was able to calculate a preliminary van count of 2.83 using the concept model that had been developed. Besides providing the desired data, management at FastWay was able to quickly alter certain parameters to experiment with the van count.

For instance, in Figure 4.7 the stop times were changed from 10 to 12 minutes. This increase indicated a 12 minute service time would cause the van count to rise to 3.10.

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Route #	Distance (Miles)	Average Speed (MPH)	Number Stops	Average Time per Stop (Min)	Total Trip Time (Min)
1	15	17	4	12	100.94
2	12	15	4	12	96.00
3	13	15	4	12	100.00
4	18	20	6	12	126.00
5	24	25	8	12	153.60
6	52	25	8	12	220.80
7	28	20	6	12	156.00
8	29	30	6	12	130.00
9	58	40	10	12	207.00
10	61	40	9	12	199.50
<b>Totals or Averages</b>	310	24.70	65	12	1,489.84
<b>Over 8 Hours</b>	<b>3.10</b>	<b>Delivery Vans Required</b>			

Figure 4.7 FastWay Spreadsheet with Modified Stop Times

Since the calculated van count is close to 3 in both scenarios, FastWay may wish to explore the option of developing a detailed simulation incorporating randomness in the delivery times, van speeds, breakdowns, and stop times. The detailed simulation would provide a firmer van count and help them decide whether three or four vans should be acquired.

FastWay has another option. They may decide to purchase four vans knowing only three are required for the route work. The fourth van can then be used as a spare, only working when one of the other three is in the repair shop or when extra deliveries are required. In this case, a detailed simulation wouldn't really provide any additional information that would impact the purchase decision. Therefore, the concept model may be the final step in the simulation process.

#### 4.3.5 Concept Modeling with Advanced Spreadsheets

A wide variety of tools and add-ins are available to make concept modeling with spreadsheets easier. The models created for the PikNGo example were developed using the Queuing Analysis ToolPak 4.0 (Figure 4.8) available without charge from:

<http://www.business.ualberta.ca/aingolfsson/QTP/default.htm>



Figure 4.8 Queuing Analysis ToolPak 4.0

Another academic version of similar software (Figure 4.9) can be found at Paul Jensen's Website:

<http://www.me.utexas.edu/~jensen/ORMM/index.html>

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Both of these sites provide add-ins to Microsoft Excel that can be installed and then used to develop a variety of concept models.

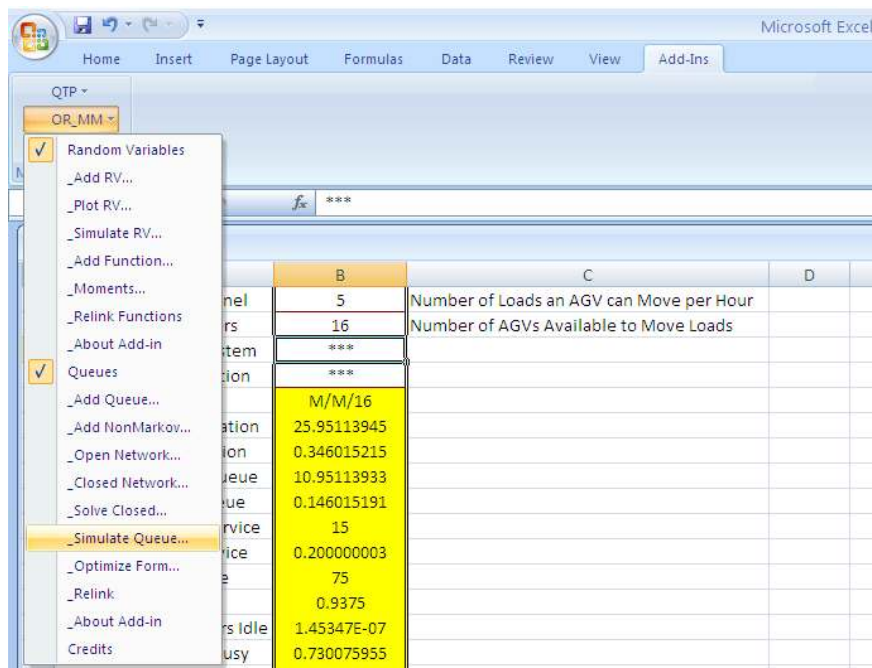


Figure 4.9 Paul Jensen's ORMM Queuing Add-ins for Excel

A variety of high quality commercial software is also available for conducting concept modeling. In many instances, a rough model quickly can be developed using a simulator or modeling software package such as ExtendSim or MedModel. Preliminary results can be quickly obtained and then used as the basis for a more detailed model after data is collected and system details studies.

Concept modeling can be either an intermediate step in a simulation process or an end in itself depending on the goals of the study. It can be used to provide quick, rough-cut information for preliminary decision making and should always be used as part of a complete simulation study.

#### 4.3.6 Scientific Method Approach to Modeling

Nearly every discipline that employs research as a tool looks to the scientific method as a means of organization. The simulation field is no exception. The following steps make up the scientific method.

- |   |
|---|
| <ol style="list-style-type: none"> <li>1. Definition of the problem.</li> <li>2. Formation of a hypothesis.</li> <li>3. Testing of hypothesis by experimentation.</li> <li>4. Tabulation of results.</li> <li>5. Drawing conclusions from results.</li> </ol> |
|---|

Table 4.5 Scientific Method

4.3.6 Model Inputs

Valid input data forms the basis for an accurate simulation. Remember the old saying “garbage in – garbage out?” A simulation will be no better than the information and assumptions it contains. Many projects have no chance for success because the input data used is not reliable (Figure 4.10).

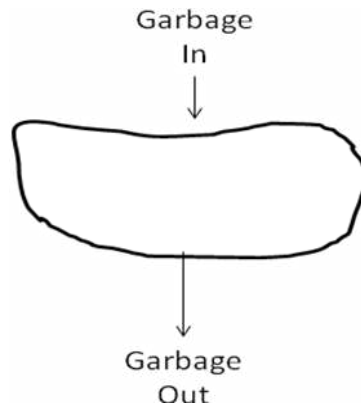


Figure 4.10 Simulation Reliability

Input data can take many forms. It can be quantitative or qualitative. Quantitative input data takes the form of numeric values. Examples would be vehicle speeds, number of cars passing a particular point on a freeway, number of tellers in a bank, acceleration rate of an automated guided vehicle or the process time at a welding station.

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Qualitative input data is a more difficult parameter to measure. It may represent the algorithms used to perform certain logical operations. In the context of the PikNGo example, if a detailed simulation were developed, qualitative values would include the rules used to determine which load to move next or what happens when a vehicle goes out of service. Will other vehicles be reallocated? Will other changes take place? If an improper qualitative assumption is made, the model may not be accurate.

Input data can be obtained in many ways. Examples of several methods follow (Figure 6.5b):

**Observation** – A good method of obtaining input data is through observation. If a model were to be made of a busy intersection in a growing city's business district, a method of obtaining input data would be through direct observation and measurement of the traffic flows. Depending on the circumstances, data might be collected by people or through using computerized equipment. Once collected, the data could be used as a direct input to the model, although generally, it is better to use the data to select an appropriate input probability distribution.

**Estimation** – If the system to be modeled does not exist, it may be necessary to estimate input data. Although somewhat less than scientific, estimation may still help provide valuable insight concerning a system's operation.

**Interpolation** – If a similar system exists, its input data can be observed and then interpolated for entry into a model sharing the same characteristics. An example might be found in a machine shop setting. Five years ago a numeric controlled (NC) machine was purchased. It was able to keep up with required production rates until the present year when sales unexpectedly skyrocketed. In light of these changes, management had to make a purchasing decision. The manufacturer of the NC machine was contacted and recommended a new model which was able to process a third more material than the existing machine. By using data based on the NC machine in current use, interpolated values were derived and the expected operation of the new machine modeled.

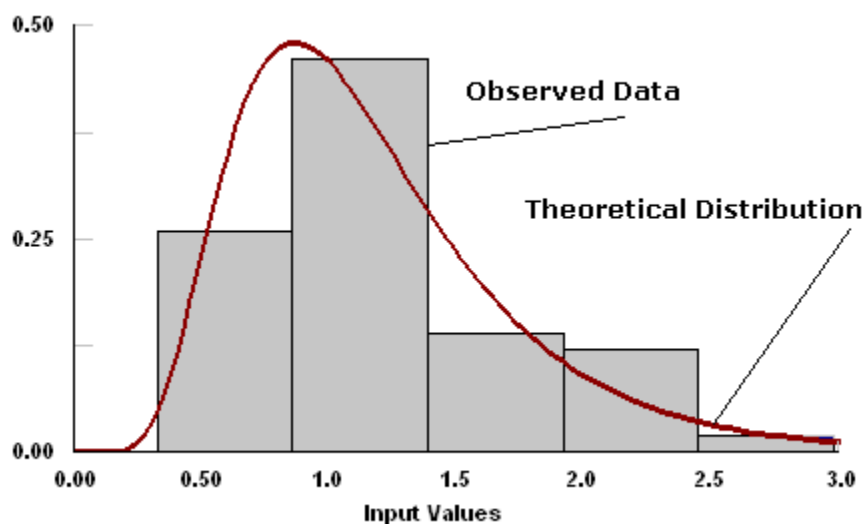
**Expert Opinions** – Many times no true data is available and so expert opinions must be used in a model. For example, an engineer who has been responsible for the operation of a warehouse over the last twenty years may be able to provide data used in simulating proposed shipping docks. Although no real data can be collected, the engineer has an understanding of how the system will need to operate.

**Projections** – Model input data is commonly derived from future projections. For instance, a Japanese auto plant has enjoyed great success in marketing its products. They keep data depicting their growth rate over the last seven years. Next year they are forecasting a required increase in production of 21% to keep up with their expected sales. By using this projection, they are able to create input data to drive an assembly line simulation they maintain.

After input data has been collected, two approaches can be taken to utilize the information in the simulation. The first approach is to use real data as is. This technique is known as a trace simulation. The second approach is to fit a standard statistical distribution to the empirical data. In this instance, it is important to find a probability distribution so that random samples taken from it will be indistinguishable from the actual collected input data. Goodness-of-fit tests can be used to statistically validate this process. The following section explores several commonly used goodness-of-fit tests. After a probability distribution has been chosen, a random number generator or a pseudo-random number generator can be used to draw samples from the distribution and drive the simulation.

#### 4.3.7 Statistical Methods and Input Data

Although empirical or “as is” data can be used for simulation input, the recommended approach is to fit a theoretical distribution to the data when possible (see Figure 4.11).



**Figure 4.11** Fit Observed Data to Theoretical Distribution

If only observed data is used, then the simulation will never be exercised beyond that which was collected. In other words, extreme or unusual situations may never occur in the model. By using a theoretical distribution, the rare, large or small incidents will occur on occasion (Figure 4.12), thereby exercising the model beyond the limits of the collected data. Using a theoretical distribution in a model can make it more powerful and predictive than standard calculations or concept models.

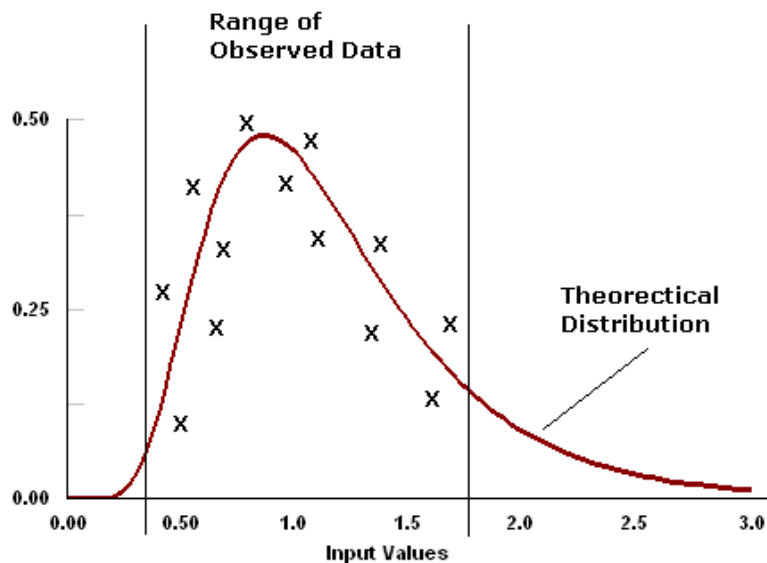


Figure 4.12 Theoretical Distribution Exercises Limits of Data

When an input variable is approximated with a probability distribution, the simulation analyst must be certain that the distribution does in fact represent the variable accurately. The first step in this process is to determine the specific form of the representative distribution. Examples of distributions include exponential, lognormal, normal and Poisson (see Figure 4.13).



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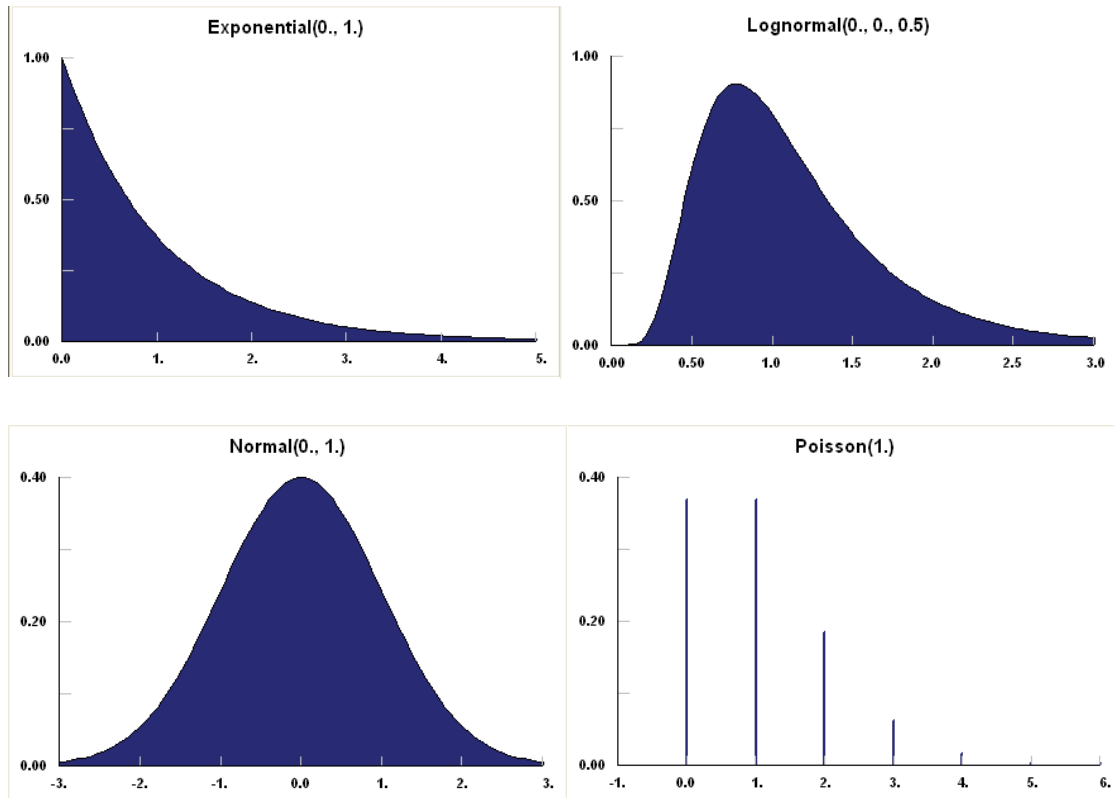
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**Figure 4.13** Example Distributions

In order to choose the proper distribution, the statistical properties of the collected data must be determined. Initially, this can be done with a visual inspection of the data in histogram form. To confirm the visual inspection, a goodness-of-fit test can be used to measure how closely the observed values match expected values. Two common methods of confirmation are Pearson's chi-square test and the Kolmogorov-Smirnov test. An example of performing a goodness-of-fit test will be provided in sections 4.3.9 and 4.3.10 but simulation analysts rarely perform goodness-of-fit tests manually. Most analysts indirectly apply these tests using features built into statistical analysis software packages that aid in distribution determination. Section 4.3.11 provides details on a more practical method for performing goodness-of-fit testing.

#### 4.3.8 Pearson's Chi-Square Test

Pearson's chi-square test can be used to assess goodness-of-fit and determine whether an observed frequency distribution is significantly different from a theoretical one. In a general sense, the chi-square test relies on calculating the chi-square statistic ( $X^2$ ) which represents the sum of the squared differences between observed data values and theoretical frequency for each possible outcome. Additionally, degrees of freedom, or number of variables that can vary freely, also must be calculated. The value of the test-statistic becomes:

$$X^2 = \sum_{i=1}^n \frac{(O_i - E_i)^2}{E_i}$$



Where:

$X^2$  is the test statistic that asymptotically approaches a true  $\chi^2$  distribution.

$O_i$  is an observed frequency;

$E_i$  is a theoretical frequency;

$n$  is the number of possible outcomes of each event.

The chi-square statistic is used to calculate a p-value derived from chi-square distribution. In general, the chi-square goodness-of-fit test should be applied to a categorical variable from a single population to determine if the sample data are statistically indistinguishable from a hypothesized or theoretical distribution. The following conditions or assumptions must be true for the chi-square test to be valid:

- A simple random sampling method was used to collect the new data.
- The population is 10 times or more greater than the sample.
- A categorical variable is being tested.
- Each level of the variable is five or more.

Then, the following steps are used to conduct the goodness-of-fit test: (1) formulate hypotheses, (2) state analysis parameters, (3) test sample data, and (4) interpret and report finding.

### **Formulate Hypotheses**

In most goodness-of-fit tests, the null hypotheses will be stated to indicate the nature of the test. For instance, the test is seeking to support the premise that the sample data are consistent with a particular theoretical population distribution. For goodness-of-fit testing, a generic null hypothesis becomes:

$H_0$ : The collected data are consistent with the theoretical distribution.

### **Analysis Parameters**

Analysis parameters include the rules for accepting or rejecting the null hypothesis. In general, the parameters include significance level and test method.

### Test Sample Data

In order to test the sample data against the theoretical population, degrees of freedom, expected frequency counts, test statistic, and p-value must be determined.

- Degrees of freedom (DF) equals one subtracted from categorical variable's number of levels (k):  

$$DF = k - 1$$
- Expected frequency for each level of the categorical variable equal sample size multiplied by the hypothesized proportion of the theoretical distribution:  

$$E_i = np_i$$
- The chi-square test statistic is a random variable defined as:  

$$X^2 = \sum [ (O_i - E_i)^2 / E_i ]$$
- The p-value represents the probability of observing a sample statistic as extreme as the test statistic.

### Interpret Results

A conclusion is developed by comparing the p-value to the significance level. If the p-value is less than the significance level then the null hypothesis is rejected.



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### 4.3.9 Example Chi-Square Goodness-of-Fit

The following scenario illustrates the chi-square goodness-of-fit test.

#### Chi-Square Goodness-of-Fit Example

A toll booth simulation is being updated. Originally, different booth configurations had been tested using a stream of vehicles expected to pass through the booths. Data representing the traffic had been collected for the original model when it was constructed five years earlier. The study used a distribution of vehicle types based on highway observations. At that time it found that approximately 10% of the vehicles passing through the booth would be motorcycles, 60% cars, 20% trucks and 10% cars with trailers. Since that time, the demographics of the surrounding area had changed dramatically and traffic patterns had shifted to a mix that represented industrial growth in the region. A small random sample of data was collected to determine if the original distribution was still representative of current conditions. In order to make this determination, the new random sample was tested against the original theoretical distribution using a chi-square goodness-of-fit test. This would provide statistical evidence that the new sample distribution either differed significantly from the original distribution or that it was essentially the same.

An analysis was performed on the following sample data (100 observations):

- Motorcycles: 5%
- Cars: 55%
- Trucks: 35%
- Cars with Trailers: 5%

A visual inspection of the data is provided in Figure 4.14.

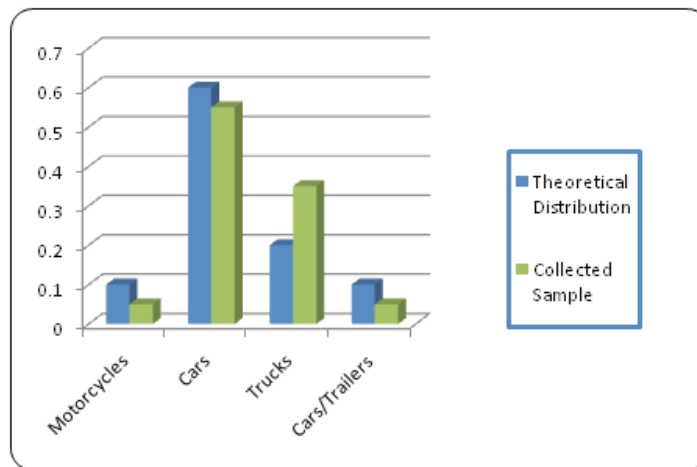


Figure 4.14 Visual Comparison between Collected Sample and Theoretical Distribution

While the distributions are similar, a noticeable difference exists that indicates a statistical test should be completed.

### Chi-Square Goodness-of-Fit Example (con't)

Hypothesis:

$H_0$ : The collected data are consistent with the theoretical distribution of 10% motorcycles, 60% cars, 20% trucks and 10% cars with trailers.

Analysis parameters:

In this analysis, a .05 significance level will be used which means the results provide a 95% confidence interval regarding the conclusion. The test method has already been stated and is the chi-square goodness-of-fit test.

Test sample data:

The chi-square goodness-of-fit test statistic and p-value for the sample data are computed as follows:

Degrees of Freedom:

$$DF = k - 1 = 4 - 1 = 3$$

Expected Frequencies:

$$(E_i) = n * p_i$$

$$(E_1) = 100 * 0.10 = 10$$

$$(E_2) = 100 * 0.60 = 60$$

$$(E_3) = 100 * 0.20 = 20$$

$$(E_4) = 100 * 0.10 = 10$$

Chi-Square Test Statistic:

$$X^2 = \sum [ (O_i - E_i)^2 / E_i ]$$

$$X^2 = [ (5 - 10)^2 / 10 ] + [ (55 - 60)^2 / 60 ] + [ (35 - 20)^2 / 20 ] + [ (10 - 5)^2 / 10 ]$$

$$X^2 = (25 / 10) + (25 / 60) + (225 / 20) + (25 / 10) = 16.67$$

p-value:

The p-value can be obtained through use of a distribution table shown in Table 4.6:

From the table,  $p < 0.001$

df\area	0.9	0.5	0.25	0.1	0.05	0.025	0.01	0.005	0.001
1	0.02	0.45	1.32	2.71	3.84	5.02	6.63	7.88	10.83
2	0.21	1.39	2.77	4.61	5.99	7.38	9.21	10.60	13.82
3	0.58	2.37	4.11	6.25	7.81	9.35	11.34	12.84	16.27
4	1.06	3.36	5.39	7.78	9.49	11.14	13.28	14.86	18.74
5	1.61	4.35	6.63	9.24	11.07	12.83	15.09	16.75	20.50

**Table 4.6** Values of X2 for Various Probabilities

A more common approach for goodness-of-fit testing is to use a distribution calculator or statistical analysis program rather than a table. Various distribution calculators can be located on the Internet either as commercial products or as freeware (see Figure 4.15). The calculator illustrated below was developed by Hans Lohninger at the Institute of Chemical Technologies and Analytics, Vienna University of Technology and can be obtained from:

[http://www.vias.org/simulations/simusoft\\_distcalc.html](http://www.vias.org/simulations/simusoft_distcalc.html)

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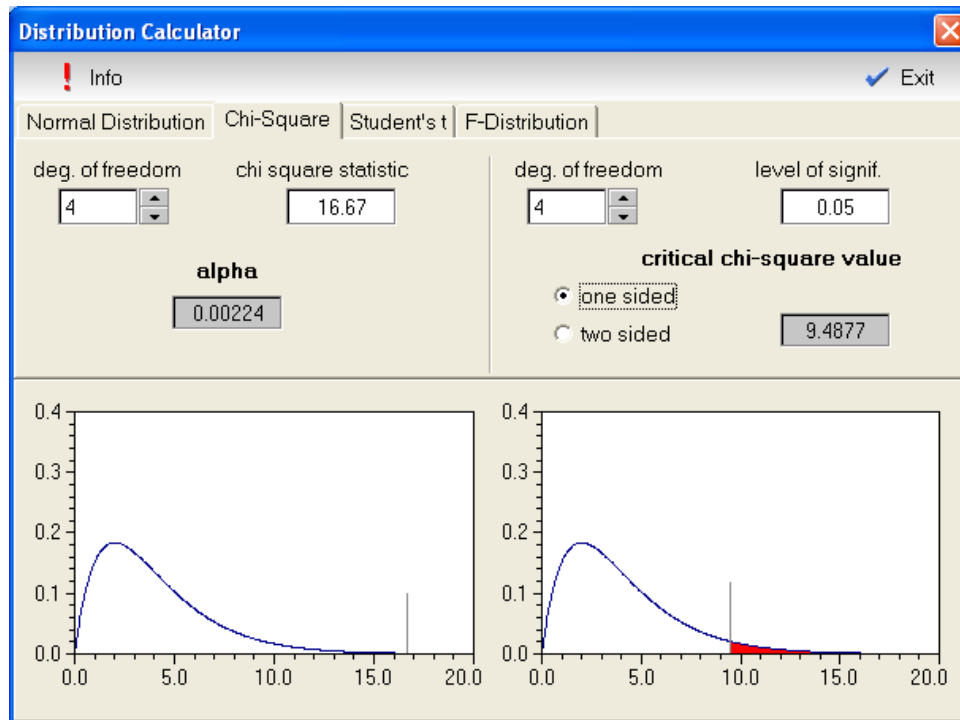


Figure 4.15 Distribution Calculator

As can be seen from both the chart and the Distribution Calendar, the p-value (.00224) is less than the significance level (0.05), therefore the null hypothesis cannot be accepted. The original data distribution cannot be used in the new simulation. A larger data sample should be collected and the input distribution must be redeveloped.

#### 4.3.10 Kolmogorov-Smirnov Test

The Kolmogorov-Smirnov test is another accepted nonparametric method of verifying goodness-of-fit between distribution function of the collected data and a theoretical probability distribution function. It has several advantages over the chi-square test:

1. Does not require data to be grouped in any way, thus keeping data from being lost or inappropriately classified.
2. No interval specification or class breakdown is necessary.

Kolmogorov-Smirnov also has several disadvantages:

1. The data being tested must be continuous. Discrete data should not be used (although it sometimes is used, particularly when estimates are being developed).
2. Parameters for the population cannot be estimated from the sample's characteristics as they are in the chi-square method.
3. It is more sensitive near the center of the distribution and less sensitive in the tails.

#### 4.3.11 Anderson Darling Test

The Anderson-Darling test determines whether a sample of collected data comes from a hypothesized distribution. It is closely related to the Kolmogorov-Smirnov test but gives more importance to the tails. Unlike the K-S test, the Anderson Darling test uses the hypothesized distribution to calculate critical values which makes the test more sensitive.

#### 4.3.12 Example Using Data Fit Software

Most simulation analysts use distribution fitting software as a means of determining suitable input distributions for their models. Two commonly used software packages for doing this are:

ExpertFit from Averill Law & Associates:

<http://www.averill-law.com/ExpertFit-distribution-fitting-software.htm>

StatFit from Geer Mountain Software Corporation:

<http://www.geerms.com/>

#### Student Union Banking Center

A Midwestern university in the United States considered opening a banking center next to its busy student union food court. As part of the cost-benefit analysis, a computer model was constructed. To accurately simulate staffing requirements, data was collected from a bank at a similar university. Data was obtained through direct observation. The analysis team clocked the arrival times of each individual as they entered the banking area, the length of time they interacted with the teller(s), and their total time in the system (which included queuing time). Approximately 50 observations were collected. In order to use the service time data in the model, Stat::Fit Version 2 from Geer Mountain Software was used to compare the collected data to over 30 known theoretical distributions and test for goodness-of-fit. Nonparametric tests were used since the collected data was not normally distributed. Stat::Fit Version 2 tests the following null hypothesis:

$H_0$ : Fit of collected data to theoretical distribution is good.

The best fitting distribution for the service time data was lognormal. This hypothesized distribution was tested against the data using both Kolmogorov-Smirnov and Anderson Darling tests. In both cases, the null hypothesis  $H_0$  could not be rejected and an acceptable fit was indicated. Figure 4.16 looks at the hypotheses tests. Figure 4.17 provides a graphic look at the collected and hypothesized data. Figure 4.18 provides additional statistical output.

The following example demonstrates how this software is used:

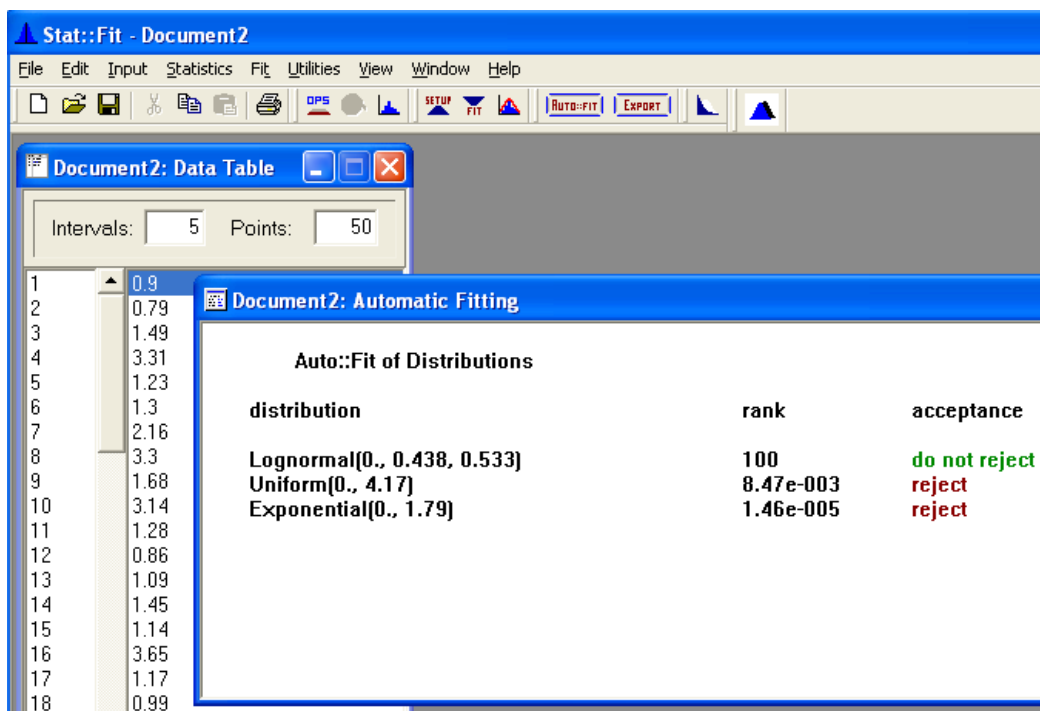


Figure 4.16 Hypothesis Tests

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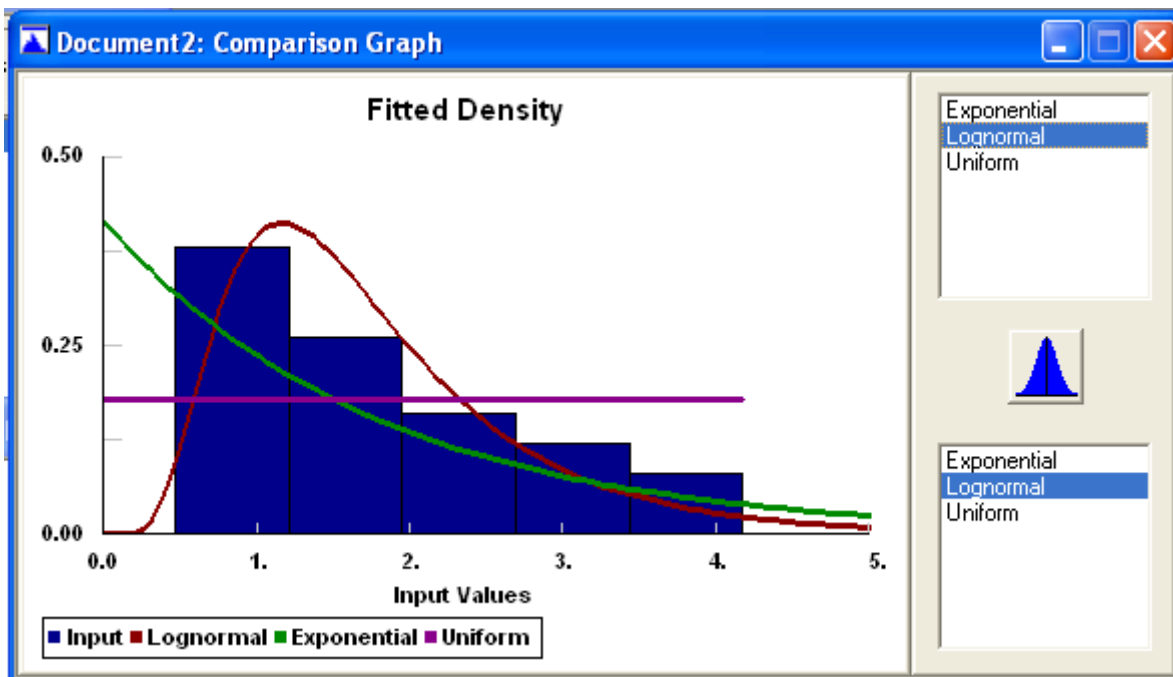


Figure 4.17 Comparison between Collected and Hypothesized Data

Comparison between Collected and Hypothesized Data

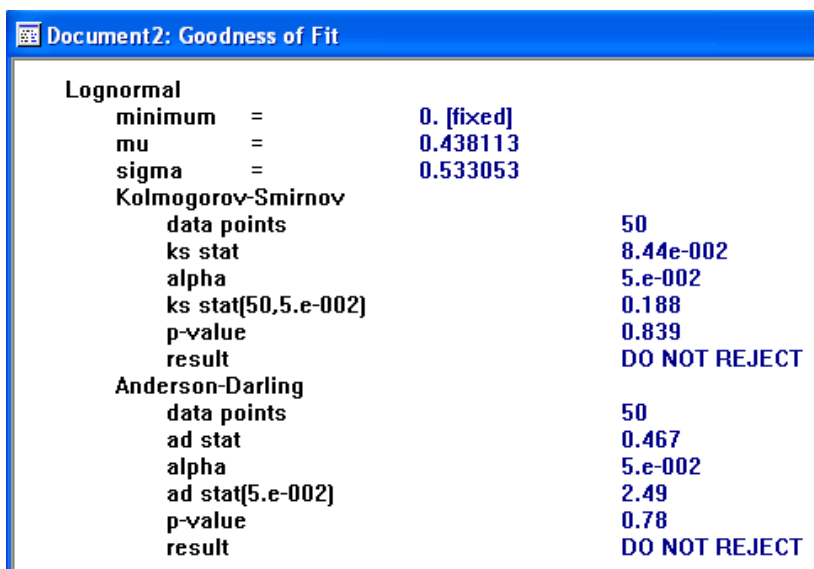


Figure 4.18 Statistical Output from Stat::Fit 2

Distribution fitting software packages such as Stat::Fit 2 often provide additional features to translate the statistical distribution into code that can be inserted into a simulation model directly. Figure 4.19 provides the code required to use the lognormal distribution tested above in GPSS.

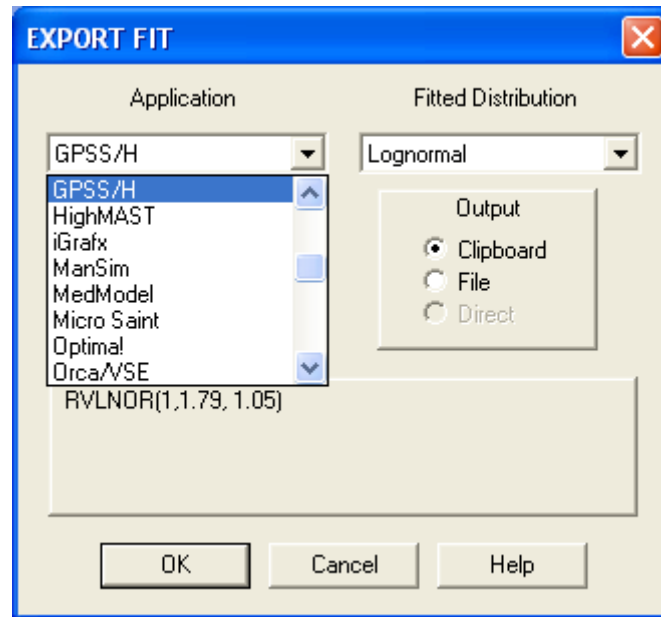


Figure 4.19 GPSS Code for Lognormal Distribution

## 4.4 Human Component Considerations

Special consideration often must be made when human behaviors are included in models. According to Brown (2002) variability due to the human factor can be attributed to at least three sources:

1. Different people may have different backgrounds and base skill levels.
2. Different people may have different levels of experience with both the system and the benchmark tasks.
3. A level of inherent variability exists in all human behavior: two people with the same training and background may still behave differently for unknown reasons.

To mitigate and manage this variability, different techniques can be used. Among these are Simplementation Cases and Persims (see McHaney 2008 for a complete discussion on this topic).

### 4.4.1 Simplementation Cases

A use case facilitates the capture of system functional requirements during systems analysis and design in traditional software development. In a use case potential users, known as actors, are documented along with their reason for using the system. This way, information captured with a use case ensures the developed system accounts for all user needs.

Use cases are part of the Unified Modeling Language (UML) and help transform unstructured user descriptions of a desired system into a more formal model. Through a conceptual extension, a use case methodology can be applied to the human element in a simulation model. This will help develop a better understanding of how that system will be impacted by the human variability and other aspects of the human component. Instead of showing how humans will use the system, the implementation case will represent how a human acts in the system. The actor is moved from interacting with the system to becoming a component within the system. Documenting simulation actors is important for several reasons:

1. Model developers are better able to see the full scope of human action within the system.
2. The places where human behavior will impact the system are more closely examined. For example, a bank teller could be represented with a single actor on the diagram but a range of personality types and behavior patterns might be required to realistically capture all the individuals that might play that role in the real world.
3. The analyst is forced to consider scaling issues in model development.

Whenever possible, each actor should be described in the context of a single implementation case. This is not a firm rule and occasionally it might make more sense to show multiple actors in a single case when the diagrams are not complicated or difficult to understand.



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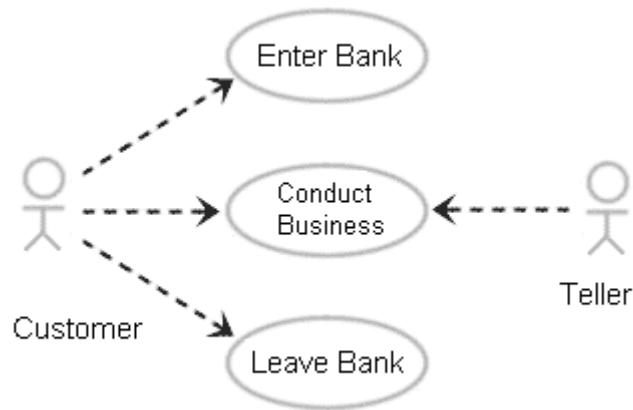
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The sum total of the implementation cases ensures the modeled system considers all human behavior within the model. Further, implementation cases become a good mechanism to organize unstructured system descriptions into formal qualitative model requirements. The actors become system components with potential for complex behaviors. Figure 4.20 illustrates.



**Figure 4.20** Simple Implementation Case Example for Bank Customer and Teller

#### 4.4.2 Persims

While general roles for the human component will become apparent during implementation case construction, the range of behaviors for these actors will not be fully documented. For this reason, and particularly in systems where the human component may have a major impact, the primary actors should be extended through the development of a construct equivalent to personas in a software development project.

In software development, personas are fictionalized descriptions of system user groups or archetypes. These archetypes are broken down by behaviors, goals, and motivations to extend use cases beyond mere function and create realistic profiles of potential users to give system developers a better sense of the system. Personas help designers overcome issues related to narrow thinking and provide contradictory views of intended groups of users.

When personas are extended for use in simulation models, they become Persims, which stands for persons that are simulated. Persims extend the understanding of the actors represented in general implementation cases and help analysts realistically scale models and better consider ranges of behavior for the human component in models.

Generally, one actor in a implementation case will represent several persims, each with their own experience and behavioral motivations within the system. If various persims can be identified and studied, then they may be represented with different input distributions and hence model scaling will become more refined and result in a more accurate simulation.

Potential persims can be obtained in a variety of ways. Among these are (Table 4.7):

- In an existing system, human behaviors can be observed and codified into archetypes.
- Behaviors can be developed from interviews, transcripts and surveys.
- Theoretical archetypes can be developed for new systems being simulated.

**Table 4.7** Ways to Obtain Persims

For instance, archetypes for tellers at the university student union food court bank might be:

1. students needing part time employment
2. spouses of professors
3. tellers from the main branch seeking a different experience

In a simplmentation case, these archetypes would be represented by a single actor but when considered in the light of their motivations and experience, each persim might behavior within the system according to a different distribution and this scaling may have a big impact on system outcomes. Table 4.8 provides an example of the three bank persims and provides a starting point for collecting data to model each.

Persim Brief Summary					
Name	Archetype	Description	Personal Goals	System Interaction Notes	Representative Portion of Group
Gabe Capman	Senior Teller	Knowledgeable, long-term employee, quick problem solver, sometimes helps other teller at the expense of his own customer's time, enjoys coffee breaks	To continue to increase knowledge and appear competent at all times, be helpful and available for answering questions, advance to a managerial position	Fast and accurate, can speed up when customer queues lengthen	20%
Neve Irenite	Young Teller	Enthusiastic, takes extra time to be friendly to customer, makes occasional mistakes, is very careful and checks work frequently	Learn the system; make fewer mistakes; be a customer pleaser	Cannot speed up when lines build, gets flustered and more mistake prone when time becomes an issue, prone to explain everything carefully to customers	70%
Bob Woffer	Unhappy Teller	Disgruntled and has plans to quit, generally polite to customers but not interested in much personal banter, avoids trying to help others, works slowly	Would prefer to enter own information regarding seminars, Wants to do things fast and not worry about transaction that didn't go through properly	Not willing to help others and often slips out when queues build	10%

Table Adapted from McHaney, 2008.

**Table 4.8** Persims Identified in Midwestern University Food Court Bank

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