3 Applications of Simulation

There has been a long running debate that concentrates on trying to decide whether simulation should be defined as an art or a science. Those who believe it to be a science feel that statistics, mathematics, and computer science comprise its foundation and are the basis for this classification. Others feel that the skill of the modeling team, the creativity involved in developing the model, and the interpretation of the results all add up to an individualized art. In this author's opinion, there is no real way to scientifically structure a simulation to guarantee that its results are valid.

Instead, after the model has been coded and run, the outputs can be studied and compared with corresponding known values to determine suitability. If no known values exist then the modeler must rely on his instincts and the judgment of experts to make this determination. The creativity and instincts used are akin to an art. Much of the methodology involved in model creation and analysis are based on computer science and mathematical principles. Therefore, elements of art and science exist in modeling. Simulation best may be defined as a "soft-science" containing both.

Figure 3.1 depicts the spectrum extending from art to science and the simulation's place. In recent years simulation has been moving along the spectrum more toward the science end. Improvements in simulation languages and the advent of simulators have removed some of the need to be as creative and innovative. Much of the uncertainty in model creation has also been eliminated through the development of application specific languages.

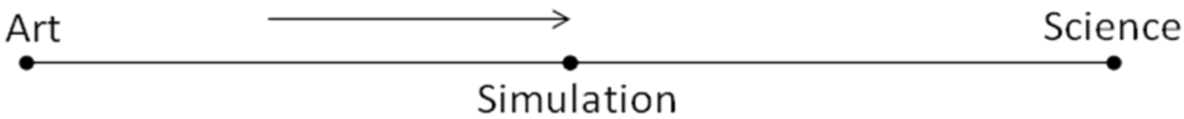

Figure 3.1 Simulation is Becoming More Scientific

3.1 Why Use Simulation

Numerous explanations exist for reasons behind the phenomenal growth computer simulation has experienced both in terms of application areas and in the number of available software products. Among these reasons are:

1. Improvements in computers: The first simulations were done on large, room-sized mainframe computers. These computers relied on card decks and operated most often in the batch mode. Not many people had access to these mammoth devices. In the last thirty years, computers have been reduced in size and cost considerably. Equivalents of the mainframes that used to occupy large rooms are now carried around in briefcase sized packages. Computers have moved from research laboratories and can now be found on practically every desk in all industries. The computing power of a single chip is fast becoming all that is necessary to run the most sophisticated commercial simulation software. This widespread availability and reduction in cost of computers has enabled simulation to prosper.
2. Improvements in simulation products: Thirty years ago, most simulation work was done using assembly language, FORTRAN, or other high level languages. Development time was much greater, as was debugging, statistic tabulation, and the reliability of results. This situation began to change with the advent of GPSS in 1961. Since that time, a multitude of simulation languages, analysis programs, animators, and pre-programmed simulators have become available. Much of the development time required to create a model has been eliminated through standard features found in these products. In addition to performing the necessary simulation functions, varying degrees of user friendliness are available. Simulation languages such as Simscript and GPSS/H appeal to practitioners with programming skills while non-programmers can enjoy the mouse driven menus found in many application specific simulators.
3. New opportunities for simulation education: Three decades ago, very few universities offered discrete event simulation classes. Today many universities offer simulation classes in engineering and business curriculums. In addition, private seminars and training sessions are available. These sessions are sponsored by simulation software vendors, consultants, and corporations with an interest in simulation and modeling. Other sources of simulation education are trade magazines, academic publications, conferences, societies, and books.
4. Increasingly complex and technical work environments: During the previous few decades the average work environment has changed from simple manual assembly lines to complex automated systems. Many repetitive human tasks have been replaced with robots and factory automation equipment. Conveyors, forklift trucks, storage and retrieval racks, as well as many other factory floor items are now routinely controlled by programmable logic controllers or computers. This new complexity has made factory output rates very difficult to predict and manage. Thus, the need for better analysis tools arose. New simulation techniques evolved to satisfy this demand and were able to remove much of the guess work and uncertainty in the work place.

5. Computer literacy among analysts and engineers: Computer literacy and use is nearly ubiquitous among professionals. Everyone has the ability to receive computer training.
6. Competition and tightening budgets – Another factor adding to growth in simulation use is an emphasis on lowering overhead costs, reducing labor requirements, and streamlining operations. Much of this has come about as globalization has increased competition and businesses compete on an international basis.
7. Realization of the benefits offered by simulation: As more industries recognize the benefits of simulation, investing in capabilities to use these tools becomes more important. Apparent economic advantages have prompted companies to invest time and resources into this area.
8. Industrial peer pressure: Organizations without simulation capabilities have found themselves at a competitive disadvantage. This was most apparent in industries, such as materials handling, where a simulation study accompanying a quotation would lend credibility to a proposed system and often become a determining factor when the contract was awarded. A situation of industrial peer pressure was created. Purchasers would inquire why simulation was not being used by their vendors and demand that some type of through-put guarantee be given. Presently, most materials handling system request-for-quotations require modeling be performed prior to purchase. Similar requirements exist in other industries. These forces have been a key factor in popularizing simulation.

9. Warm fuzzy feeling: Many companies have developed internal simulation groups to model in-house problems, proposed systems, and existing manufacturing processes. Presentation materials such as simulation animation packages have helped to sell internal proposals to management and create a corporate warm fuzzy feeling. "Seeing is believing" and many simulation packages available today place an emphasis on graphics and output.
10. Part of an effort to increase quality: Another force related to simulation adoption is a commitment to quality improvement processes. The success of these philosophies has been demonstrated in many industries with large productivity gains and improved profitability. A major precept of quality is prevention of problems. By creating a model of systems to be designed, purchased, or installed, costly mistakes can be avoided and installations can be done right the first time.

3.2 Simulation as a Design Tool

Depending on the application area, simulation can be used for different purposes and to answer a variety of questions. It is important to know what information the simulation is to provide at an early stage in its development. This ensures sufficient detail is incorporated into the program and helps to prevent developing inappropriately scaled models.

In addition to application area, the stage in the simulation process determines what questions should be asked. For example, early in the study answers to broad scale questions may be sought. General feasibility is often determined with a simplified version of the model. If the system performs as desired in this stage of the project, then more detail can be added and different types of information can be sought. Simulations of the preliminary nature are often performed with spreadsheet programs, rapid-modeling tools or simulators. Table 3.1 provides examples of questions that may be asked at different stages in the simulation process.

1) Preliminary Stages (global questions of feasibility):
   Do we have sufficient plant capacity?
   Is this type of system feasible for use in our application?

2) General Strategy Questions:
   Would an Automatic Guided Vehicle system or Monorail be more appropriate?
   Should a Just-In-Time inventory scheme be employed?

3) Specific Design Questions:
   Can the chosen conveyor move enough parts to station A per unit time?
   Are these work cycle times fast enough to keep up with the product flow?
   Should a single queue feed the four stations or should one queue feed all four?

4) Fine Tuning:
   What is the optimum number of Automatic Guided Vehicles to run the system?
   How may queue positions would be best at this work station?
   Should employee coffee breaks be staggered?

Table 3.1 Simulation Questions

Questions such as these are both application specific and project stage dependent. It is important know a simulation's purpose and keep sight of its goals throughout the process.

3.2.1 Types of Simulation

During the early stages of a simulation process when broad conceptual questions are being investigated, it is advantageous to use fast, less detailed modeling techniques. When these global concerns are resolved, the model can be refined with more detail until a complete understanding of the problem is gained.

A less detailed first run simulation is commonly called a concept simulation, rough cut simulation, or rapid model. This type of model tests overall concepts without the addition of finer details. Not only does a concept simulation save time, it also gives the modeler insight regarding problems needing more work when the detailed analysis is conducted. The model simplifications often make it possible for changes to be made faster and with less effort. This allows different alternatives to be tested in a short amount of time.

Concept simulation does have pitfalls. In order to simplify the model, detail is sacrificed. This means that the results can be inaccurate. Depending on what simplifications are made, models can be made completely invalid. Crucial factors should never be oversimplified.

Concept simulation is most applicable in situations where similar systems are modeled frequently. For example, the manufacturer of monorails might use concept simulation to provide potential customers with a general system picture. Since this particular vendor has simulated and built many monorails in the past, he can be fairly confident that he has not detrimentally over-simplified the system. A budget price can then be calculated without ever performing a detailed simulation. If the customer likes the concept and the price, the simulation can move to a new stage of development where additional detail is added.

Detailed Simulation generally follows the completion of a concept simulation. Here, the model is ready for the addition of finer details. There are two ways of accomplishing this. The first method is to rescale the existing concept simulation. The second is to develop an entirely new model, using what was learned in the concept simulation. It is common to choose the second alternative for several reasons. The concept simulation in many cases is written using a spreadsheet, simulator, or rapid modeling package. The development of a more detailed model will often require a simulation language or more complex simulator be employed. This will provide the modeler with the necessary flexibility to enhance his simulation.

In this phase of the modeling process, the simulation analyst would work very closely with engineers, system experts or system designers. Actual measured distances, carefully calculated work cycle times, and scheduling algorithms would be utilized. Realistic stochastic probability distributions would replace the estimated deterministic times used in the concept simulation. Machinery down-times, repair rates, and other system inefficiencies would be added. The model would be run, tested, and either compared to an existing similar system or examined by experts for correctness. By the time the detailed simulation was complete, the entire system being modeled would be defined.

3.2.2 Operational Changes and Follow-up

After a real world system has been installed, parameters estimated in the model can be validated through measurement. For instance, a manual assembly operation expected to take three minutes may actually take four. The simulation should be updated to as theoretical values are replaced with actual measurements. If the model is maintained in this way, it can be used in the future to test the impact of desired (or undesired) changes to the system, to estimate daily production, or as part of a larger overall simulation.

3.3 Estimation of Simulation Time

Many simulation projects in industry are completed within the context of a job contract or departmental budget. Consultants, materials handling vendors, even in-house simulation departments are usually obligated to provide an upfront estimate of time the project will require. This makes an accurate prediction of the expected time frame essential. Since simulation is based on the analysis of processes that are unknown, potential problems, requiring additional analysis time, can easily arise. Therefore, an accurate estimate of time can be a difficult value to determine.

When simulation projects overrun their allotted time, usually one of the following scenarios is to blame:

1. Unexpected problems are uncovered with the model and then it is used to find solutions: A function of simulation is to detect unexpected problems and help test potential solutions. Whether large numbers of problems or even a single, complex problem are found, required simulation time can increase drastically. When completion time has been estimated for the simulation, the importance of recognizing potential problem areas of the system and the addition of time for these areas is essential. A solution to this common dilemma is to set an initial time frame for modeling the system as it has been designed. If problems are found requiring additional simulation time, a new end date can be determined. In this way, the end date would extend on an "as-required" basis.
2. The simulation customer wants "just one more scenario tested": A tendency exists to keep playing different "what-if games" once a model has been created. This tendency can lead to creative and innovative enhancements to a system but it can also extend simulation project time and cause deadlines to be missed. When estimating time for a simulation project, areas that can be changed and "played" with should be identified as being experimental variables. Extra time can be added into the estimate up-front that takes into account the desire to try several different ideas after the initial model is complete. Once the estimated time is used up, no more "what-if games" should be allowed unless extra time is purchased or approved.
3. The system is more complex than expected: Sometimes an initial inspection of a system does not reveal all of its hidden complexities. What may appear to be a straight forward process may in fact be very complicated. For this reason the estimator must be certain that he or she fully understands all aspects of the system to be simulated.
4. The simulation analyst lacks experience: Another reason for estimates exceeding their time frames is the lack of experience by the simulation analyst. On a first time project, extra time has to be included to allow the analyst to learn the simulation language, hardware, and experimentation methods. It is generally not possible to build a first time model without experiencing some delays due to the learning curve. Once the simulation team has a few projects under their belts, these delays will no longer be a factor.
5. Too much non-essential detail is included: The construction of a simulation requires that the analyst know what information is being sought. By having a question to answer, the system can be broken into essential and nonessential subsystems. This is called scaling. The key subsystems can be modeled in detail and the other subsystems can be modeled in less detail. By taking this approach, the model will remain realistic while conserving development time and effort.

The following example illustrates breaking a system into essential and nonessential subsystems. In this scenario, the assembly department in a large manufacturing plant would like to speed up operations by automating a welding operation with a robot. The system will consist of a forklift truck dropping the work piece on a conveyor. The conveyor moves the piece to the welding robot. When the operation is complete, the work piece moves on to a manual station for grinding and deburring. It is then removed from with a crane and placed into a crate for shipping. See Figure 3.2.

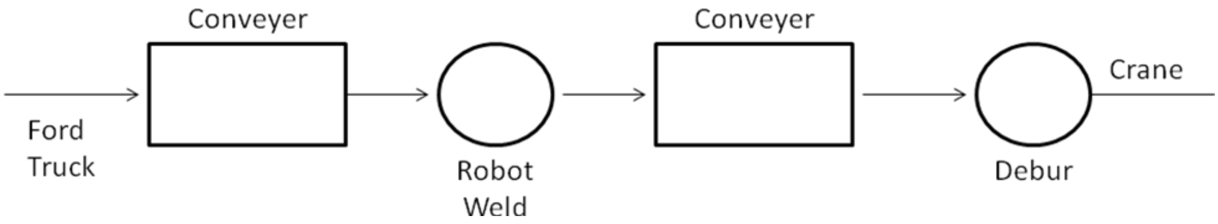

Figure 3.2 Automated Welding System

The goal of the simulation is to determine if the robot's work cycle time will be fast enough to process twelve work-pieces per hour. The system to be simulated can be broken into these components:

1. Forklift truck
2. Conveyor to robot work station
3. Robot weld operation
4. Conveyor away from robot work station
5. Grinding and deburring operation
6. Crane move to shipping crate

The most essential subsystem to be modeled is the robot weld station. It should be done in detail. The conveyor system to and from the robot may have a significant impact so it also should be modeled in detail. The grinding operation is manual. Workers can be added if needed, so it does not need to be modeled to the same level of detail. The crane operation will not be modeled in detail because unmoved work pieces do not slow down the grinding operation. See Figure 3.3.

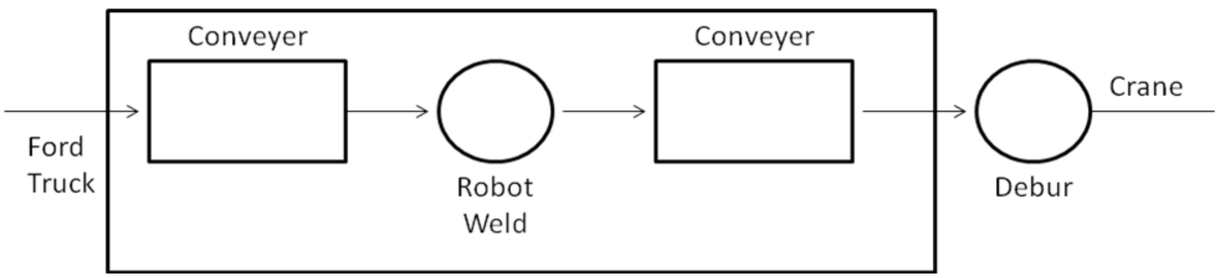

Figure 3.3 Automated Welding System Detailed Area for Simulation

By breaking the system into subsystems and defining the necessary level of detail, the goals of the simulation can be met and time can be conserved.

In the business world or manufacturing sector, it is important to be able to predict the length of time creating a simulation model will take. Some factors to consider when doing this are level of detail desired, size of simulation, project objective, and simulation software language being used.

3.4 Methodology for Manufacturing Simulations

In the manufacturing sector, a simulation methodology incorporating both concept and detailed simulation is frequently used to facilitate the design, selling, and installation of materials handling and other industrial equipment. This methodology can be summarized in the following six steps developed by Wesley Cox (see Table 3.2):

Step #	Step Name	Description
1	Concept Simulation	The creation of alternate models to test the most promising of the possible materials handling solutions.
2	Acceptance of Concept	The prospective customer accepts what she/he feels is the best alternative. Price, functionality, and through-put requirements are considered.
3	Engineering Design	The simulation is redone by adding details and final design parameters.
4	Operational Changes	Final changes are made to accommodate the changing requirements of the customers. The changes are simulated and tested for cost effectiveness.
5	Final Report	A final simulation report is provided and, if contracted, a system animation.
6	Maintenance	If desired, the simulation is maintained throughout installation of the system. Any changes or required modifications are incorporated into the model and the impact on the system is tested.

Table 3.2 Manufacturing Simulation Methodology

3.5 Forcing Completion of Design with Simulation

Due to the nature of most simulation studies, model creation will be among the first few activities slated for completion in the broader life cycle of a development or construction project. Simulation is a process which requires that all aspects of a system be considered and planned. To create a model, information must be gathered from a variety of sources and compiled for use. This gathering process will often bring different people and ideas together for the first time. Communication between persons with responsibility for the different parts of the system is facilitated.

Subsystem interface points will be discussed and obvious problems will be eliminated. Common goals will be set. Aspects of the system which were not previously considered may come to light. The formulation of creative solutions and innovative ideas may evolve. By the time the simulation is ready to be coded, very few unknown variables will remain.

3.6 The Simulation Decision

"To sim or not to sim?" that is the question.

In many companies the decision to use simulation is one that requires careful thought and an investment of thousands of dollars. For the company that has a simulation department in place, the question takes on a different meaning. It means 'should this particular problem or system be modeled?' Since simulation is expensive and time consuming, its use must be framed within the proper context. The possibility of over-modeling exists. Simulation should not be used until other methods of analysis have established the system being studied is viable. The following steps can help prevent the problem of over-modeling:

1. Make sure conceptual designs are complete and viable: An important step in system development is the forming of overall concepts. Simulation can be used to test a concept or it can be used to compare different concepts. Before simulating, ensure concepts are complete and can be used if found to be workable.
2. Look for obvious bottlenecks: Don't simulate a system that obviously can't work. Many bottlenecks can be spotted before the modeling effort begins. These evident problems should be resolved prior to simulation so extra effort and costly delays are avoided. While a system is being simulated, the analyst should continue to look for bottlenecks for the same reason. The sooner a problem comes to light, the sooner it can be dealt with.
3. Make sure a simple mathematical solution does not exist: Before the modeling process begins, use mathematics to answer questions. Not only can many situations be understood deterministically, time spent and costs may be lower.

3.7 Make It Work Vs. Does It Work

A simulation project will be conducted differently based on its overall objective. Two common objectives are: answering the question "does it work?" and taking on the task of "making it work." See Figure 3.4.

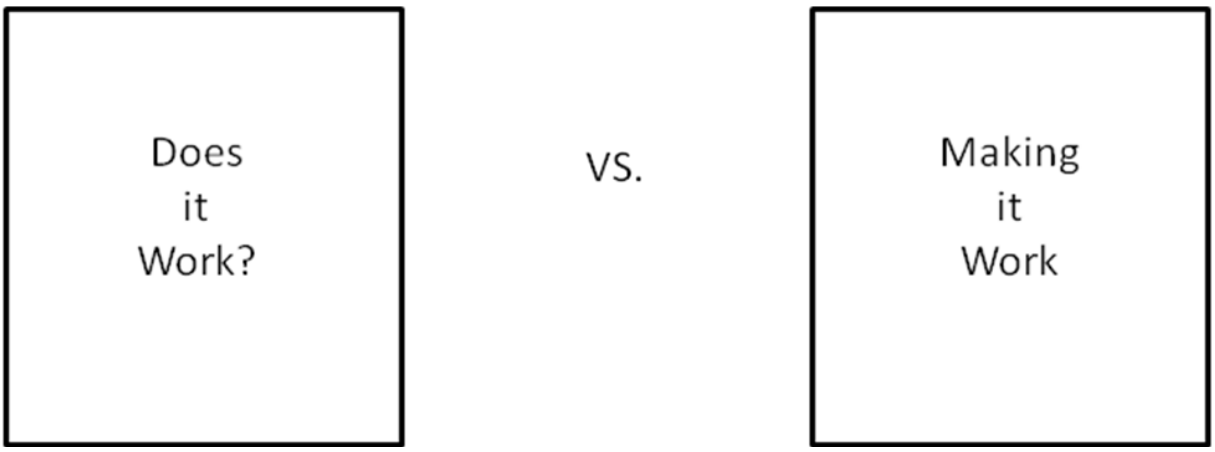

Figure 3.4 Simulation Project Objectives

Does It Work? – This project objective is clear cut and implies a model is to be used to evaluate a concept and determine if it meets a performance objective. Often the "does it work" question is used to test various alternatives for comparison. The simulation results will provide a yes or no answer to the problem being modeled. The "does it work" objective is usually easier to estimate and involves little "what-if" scenario testing.

Stamping4Success Simulation #1
A stamping machine that was purchased several years earlier became a point of controversy at Stamping4Success. Not enough work pieces were being processed each day to meet the requirements of a new contract. Management pointed its finger at machine operators saying they weren't doing their job fast enough. The operators in turn pointed their fingers at the machine saying it couldn't stamp the parts fast enough. A stalemate developed. As a means of resolution, a simulation analyst created a model of the process. The objective was to determine if the machine was fast enough to perform the required work. In other words, the model had the "does it work" objective.

Making It Work – The "making it work" objective is used when a problem exists and the simulation analyst must experiment with the system until a solution is found. Estimating an accurate completion date for models with this objective can be very difficult. It is not known prior to the simulation process how many different scenarios must be investigated before a solution is discovered. The Stamping4Success example is continued.

Stamping4Success Simulation #2
The initial simulation was completed at Stamping4Success and it showed management was correct on their assumption that the machine was fast enough to process enough work pieces to make the new contract's quota. But, the model also revealed an additional problem. Although the stamping machine was fast enough to process the parts, the system delivering the work pieces to the operators was not fast enough to keep the machine busy. A decision was made to authorize a second simulation study. The new model would have the objective of "making it work". The simulation analyst, working with a plant engineer, was told to keep trying different delivery schemes until a workable solution was found.

3.8 Optimizing and Developing Solutions

A widespread misconception about simulation involves its output information. Often, people new to simulation will imagine that their model will not only solve the problem but also provide an optimal solution. This is not necessarily, nor even ordinarily, true. Simulation can be used to optimize system performance but only in conjunction with the careful design of the proper experiments.

In many simulation studies, especially within the context of a manufacturing environment, only several feasible alternatives exist. These alternatives can be ranked subjectively in order of preference, cost, and performance. The most desired solution is simulated first. If the system does not perform at the required level, the next alternative on the list is tried and so forth until a workable solution is discovered. Use of this methodology is not scientific and will not optimize performance, but it is very practical and will result in an acceptable outcome.

If a list of possible solutions is difficult to rank and an optimal result is desired, common methods of experimental design can be employed. The first step is to identify the model's factors. Factors are defined as input parameters and structural assumptions. These factors can be quantitative and represent a specific numeric value. They may also be qualitative, representing the structural assumptions of the model. An Automatic Guided Vehicle programming algorithm is an example of a qualitative factor.

Whether the AGV picks up the closest or oldest load is a structural assumption used in the model. Factors can also be identified as either controllable or uncontrollable. Controllable factors are ones which can be changed or managed to help improve system performance. The number of AGVs used in a warehouse simulation is a controllable factor. Uncontrollable factors are ones which can't be changed within the context of the model. An example of an uncontrollable factor is the AGV's top speed.

The second step in optimizing a solution is to use viable combinations of the controllable factors as inputs in different simulation runs. The model can be run and the output performance measured. This output is termed the response. The varying responses can be screened based on meeting a minimum acceptable performance level. Experiments falling below this level will cause that potential solution to be dismissed.

The final step in optimizing the solution list is to employ some method of analysis to rank the list of acceptable factors and their responses. It may be possible to do this through inspection, by using methods of linear programming, or based on some other criterion. When the ranking process is complete, the model with the best combination of inputs and outputs will be chosen as optimal.

3.9 Genetic Algorithms

Other techniques such as incorporating genetic algorithms into a model also can be used for optimization. The genetic algorithm is a search algorithm based on the mechanics of natural selection and population genetics. These algorithms combine machine-learning with the principles of survival of the fittest. While genetic algorithms are not developed specifically with optimization in mind, minor modifications often result in adequate optimizers. Genetic algorithms work with populations of solutions and attempt to guide a search for improvement through survival of the fittest. Each potential solution is compared to a fitness function and is deemed eligible to propagate or is terminated. Over time, stochastic processes encourage the fittest solutions to emerge.

The genetic algorithm relies on a creation paradigm resembling biological reproduction. Artificial creatures comprised of binary strings are created in software. The combination of bits encoded in each string is a potential solution to a problem. These strings are stored and manipulated in computer memory.

The initial population of strings is created randomly. This population is compared to an objective function. Variations in the individual strings result in varying degrees of fitness. The fitter solutions are given a higher probability of survival and thus have a greater chance of passing their characteristics to future generations. Surviving strings form the basis for a new population. Subsequent generations are formed through reproduction, crossover and mutation. Reproduction means a string is directly copied from one generation to the next. Crossover combines characteristics of two or more strings much in the same way that a child inherits genes from his/her parents. Mutation involves small local changes such as the flip of a bit. Reproduction and crossover are the driving forces behind continual improvement of the population while mutation allows wider exploration for new solutions.

3.10 Ethics in Simulation

All designers, managers, programmers, analysts and engineers will confront issues that require ethical judgment. Occasionally this issue will be related to a simulation study. Often, a great deal of trust is put into a simulation study. The analyst must produce answers to questions that may involve large expenditures, vendor selection, designer prestige, and whether a system may even be purchased. Due to the nature of simulation studies, an analyst may be faced with a dilemma similar to the following examples:

Scenario #1:

A project manager says, "If this simulation proves that our new concept will work, the buyer will select us as vendor for sure. This contract could mean millions in new revenue and a dozen new jobs. Plus, it could mean a big raise for you and a great commission for me." After completion, simulation proves the system falls short of desired performance. The project manager is informed and says, "Find a way to make the system work by Friday." Friday arrives and the system marginally falls short of production requirements. As a simulation analyst do you create a report saying it works (and hope a solution comes to light prior to system installation) or do you stand by the model's results and report that it won't work knowing that your company's bid will not be selected?

Scenario #2:

The designer on a materials handling project would like to persuade her system team to agree with her conceptual idea regarding system operation. She asks you to "color" the simulation's output data to give her argument additional weight when the concept is presented. "It won't really change anything," she says. "It will be easier to justify my idea and get the team onboard a little faster."

Scenario #3:

A salesman reported to the simulation department that all other vendors bidding on a hotly contested job proposed eight robotic work stations be used. An in-house simulation study revealed that only five were required to produce the number of parts needed by the potential customer. The salesman suggested creating a simulation report that recommends seven stations in order to make the sale larger. The bid would come in at a lower price than the competition but extra profit would be quietly made.

Scenario #4:
A potential customer's rush order is waiting for the completion of a simulation study. After getting the base model running but before validation and proper output analysis can take place, the project team leader demands a report. In spite of the simulation analyst's objections that model validation and proper output analysis will require several more days, the team leader replies that he doesn't care and wants whatever is complete now.

The following list is advice concerning ethics in simulation. It is compiled from the opinions of several seasoned simulation analysts.

1. Simulation should never be used to misrepresent data.
2. Simulation should never be used to mislead or as a means of false justification.
3. The simulation analyst should always conduct experimentation objectively.
4. The simulation analyst should always be truthful in reporting.
5. The simulation analyst should be careful to avoid allowing her or his optimism or pessimism color reports.
6. If a mistake is made, take immediate action to rectify the problem. Never cover it up or hope it remains unnoticed.
7. If a system marginally doesn't make the required production rate, report the results together with an error margin and participate in a decision of whether the results are close enough to warrant the risk of implementing the system.
8. Ensure results are accurate through verification and validation activities.
9. Work closely and openly with the users of your model.

As a simulation analyst, you never want to be in a position where you must explain why your "supposedly valid" model meets production when the real-life system is found not to work. Fixing the system after installation is very expensive. By adhering to a sound code of ethics, a simulation analyst is able to ground themselves with a set of guidelines that will help make difficult decisions. Although the analyst's actions may not always be popular, they will be consistent and defendable. In the long run, your peers will respect your professionalism and long term view of organizational quality.

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