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INTRODUCTION TO SIMULATION

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ABSTRACT

With proper training and "de-mystification," simulation technology is becoming a widely accepted ***world class planning*** and ***problem-solving tool***. The success of a simulation project is directly related to the ***simulation knowledge*** shared by its participants, and by those who will be impacted by the results. This tutorial specifically presents the essential information to enable an individual to acquire an elementary understanding of discrete event simulation, given business and educational *time* constraints.

1 WHAT IS SIMULATION?

Simulation is the art and science of creating a representation of a process or system for the purpose of experimentation and evaluation. It is a powerful analytical tool that can significantly facilitate the problem-solving process.

Most engineers, managers, and designers are familiar with the five basic steps of problem-solving. They are: *1) Define the problem, 2) Collect data and analyze it, 3) Search for alternatives, 4) Evaluate each alternative to determine which is best with respect to performance criteria,* and *5) Implement the selected alternative and follow-up.* These are the same steps used in a simulation analysis.

Simulation is a tool that can help determine which candidate solution is optimal with respect to a desired outcome. The selection of a candidate solution requires the following steps: *1) Establish the criteria for evaluating performance and their relative weights, 2) Predict the performance of the candidate solutions with respect to the criteria,* and *3) Compare the candidate solutions on the basis of the predicted performances* [Krick 1976].

Simulation is a tool for predicting performances of possible alternatives. It turns data into knowledge, and knowledge into experience.

2 APPLICATION AREAS

The use of simulation as a problem-solving tool continues to expand. Manufacturing, chemical and food processing, distribution systems, communication networks, transportation, service industries, military, and computer systems are viable candidates for simulation analyses. Application areas are only limited by the imagination of the user.

Many manufacturers of simulation software have user groups that meet on an interim basis. These groups give users an opportunity to share the successes of their simulation efforts. They are also an excellent source for potential simulation users to obtain information pertaining to the benefits that can be achieved with simulation.

3 WHY SIMULATE?

Strategies for making continuous improvements are being implemented across all industries. Business Process Reengineering, Total Quality Management, Continual Measurable Improvement, and Statistical Process Control are just a few of the many techniques being applied. They all have as an essential element the need to evaluate ideas for improvement. In other words, one must be able to predict the performance of alternatives in order to make wise decisions.

The importance of prediction in the management of any system is well stated by Dr. W. Edwards Deming, "Management of a system is action based on prediction. Rational prediction requires systematic learning and comparisons of predictions of short-term and long-term results from possible alternative courses of action" [Deming 1989]. Simulation provides us with a tool for making these predictions.

Most of today's systems are *dynamic* and *stochastic* in nature. A dynamic system implies action. Factors that influence a system can change as time progresses. For example, a manufacturing system is subjected to part scheduling changes, equipment breakdowns, and test failures. *Stochastic* suggests that these changes can vary indiscriminately. Simulation can account for the effects of variances occurring in dynamic and stochastic systems. Conventional analytical methods, such as static mathematical models (e.g., spreadsheet analyses), do not effectively address this issue.

Performance calculations derived from *static mathematical models* are generally based on constant values, and the constant values are based on averages. An average production rate of four hundred parts per month, an average time between failures of 60 hours, and an average assembly cycle time of two hours are typical examples. Performance computations based solely on mean values neglect the effect of variances. Disregarding this factor can lead to erroneous conclusions.

What is the impact when something occurs in relation to other incidents? What if a machine malfunctions at a time when no labor is available to repair it? The fact that a machine is non-producing an average of ten percent of its total operating time does not account for the repercussions that might occur based on *when* it is non-producing. The consequences of breaking down are greater during peak production demands than during low production demands.

Simulation investigates the consequences of variances. It assesses the ramifications of random changes occurring in a system relative to some objective. The inter-relational characteristics and interdependencies of people, equipment, methods and material are examined as they evolve through time. The behavior of a system is described in terms of discrete, and/or continuous events occurring within it.

Another benefit of simulation is its ability to unite the ideas and proficiencies of numerous people. When executed properly, the simulation model building process brings together a broad scope of knowledge, information and expertise from a variety of sources. The questions, problems and concerns from multiple viewpoints are unveiled. A better comprehension of a total system is gained because the interdependencies of all components are shared and understood by all parties contributing input to a model. People become a team working together towards a common goal.

4 SIMULATION TERMINOLOGY

As with any technology, understanding the terminology is essential. Some elementary simulation definitions are as follows:

A ***system*** is an organized group of entities such as people, equipment, methods, principles, and parts that come together and function as a unit.

System state is the collection of all variables, stochastic (can change randomly) and deterministic (not influenced by probability), which contain all the information necessary to describe a system at any point in time [Smith 1989].

Discrete event is an instantaneous action that occurs at a unique point in time. An airplane landing at an airport, a part arriving at a delivery dock, a customer arriving at a bank, and a machine finishing a cycle are examples of discrete events. The occurrences of these events can cause system states to change.

Continuous event is an action without cessation. It continues uninterrupted with respect to time. The temperature of water in a lake raising and lowering during a day, the flowing of oil into a tanker, and chemical conversions are simple examples. Continuous events involve a time rate of change.

Static simulation models refer to models that are not influenced by time. There is no simulation clock involved. Seconds, hours and days play no role in a model. The state of a model does not change with respect to time. A simulation model that imitates the roll of a die is an example. The output of the model (1, 2, 3, 4, 5, or 6) is not affected by time.

Dynamic simulation models are models that are influenced by time. The state of a model evolves over simulated seconds, hours, days and months. A mathematical clock is used to track simulated time.

Stochastic simulations contain stochastic processes. Stochastic processes are composed of a sequence of randomly determined values. Time between failures on a piece of equipment is an example of a stochastic process. The time required to repair the equipment is another. Time values for both can change indiscriminately with each occurrence.

Deterministic simulation models are any models that do not contain random variables. Results produced by this type of model are not influenced by probability. An example is a model that solely utilizes constant average values to represent the functions and characteristics of its entities.

Steady-state condition implies that the system state of a simulation is independent of its initial start-up conditions. Analyses from steady-state simulations are based on output data generated after steady-state conditions are achieved. The cumulative average of multiple die rolls can be used to demonstrate a steady-state condition. After a certain number of rolls, the cumulative average of all values rolled will remain at approximately 3.5. The point at which this occurs exemplifies a steady-state condition.

Terminating simulations run for a predetermined length of time or until a specific event occurs. Analyses and conclusions are based on output values produced at the stopping point.

Warm-up periods are the amount of time that a model needs to run before statistical data collection begins. It is the time period required for a simulation to reach a steady-state condition.

Random number streams are a sequence of random numbers where each succeeding number is calculated from the previous number derived. The initial number is referred to as the random number seed. Random numbers with values between zero and one play an important role in extracting values from probability distributions.

Model runs involve operating a simulation for a specified period of time with a unique set of random values. An ***independent model replication*** entails operating the same model for the same period of time with a different set of random values.

5 HOW DOES SIMULATION WORK?

Simulation, like most analytical studies, describes a problem, process, or system in terms mathematical variables. Discrete event simulation modeling is the processing of a repetitive set of instructions. The instructions define how the values for variables can change in relation to changing conditions. Conditions change because of the occurrences of events. A part arriving at a machine or part leaving a machine can be considered an event. A machine breakdown is another example of an event. As each event occurs, a set of actions (computations) is performed pertaining to it.

A *dynamic* and *discrete* event simulation model performs a repetitious sequence of instructions similar to the following: *1) Determine what event type will occur next, 2) Set a simulation clock variable equal to the time of the next event 3) Update any statistical variables where required, 4) Perform the actions (computations) associated with the most current event, and 5) Schedule a time for the next occurrence of that event type.*

Computers are programmed to perform the various instructions. A drawback in the past was the effort required to translate the instructions into a computer language. This was usually a formidable task in the early days of simulation. Today this is not true. The translation (code writing) process has been substantially simplified with most of today's simulation packages.

It is now possible to build models with little or no knowledge of the code writing logistics, and mathematics involved with simulation. However, it is still beneficial for simulation users, management, and project participants to have an elementary appreciation of the principles governing the reasoning and computations used with simulation. Results can be misinterpreted when their derivations are not understood.

6 SIMULATION SOFTWARE

There are many simulation software packages available on the market today. Most are classified as simulation languages or simulators. The differences between the two are becoming less and less. A primary goal of most simulation software manufacturers is to make simulation easier for the user. They have, and are continuing to do an excellent job in accomplishing that goal.

The selection of a simulation package should be based on the specific needs of a user. Finding a package that will ultimately satisfy your requirements is best accomplished by experimenting with multiple packages to investigate their individual qualifications as compared to your needs.

7 PROBABILITY DISTRIBUTIONS

Probability distributions are the bases for generating stochastic behavior (random variates) in simulations. A probability distribution is a set of values or measurements that relate the relative frequency with which an event occurs or is likely to occur. They can be derived from empirical data collected from a selected process. In general, any process that repetitively produces outcomes that vary from one occurrence to another can be represented with a probability distribution.

Standard probability distributions are often used to represent empirical data distributions because they help "level out" data irregularities which may exist due to values missed during times of data collection. Values not observed during data collection periods can be accounted for by using standard distributions representative of the observed data.

There are several standard probability distributions that are frequently used with simulation. They include: the *Exponential, Gamma, Normal, Uniform, Weibull, Triangular, Lognormal, Erlang,* and *Beta* distributions. The use of one standard distribution over another is totally dependent upon the empirical data that it is representing, or the type of stochastic process that is being modeled (when no data is available).

Statistical analyses must be performed on empirical data to find a standard distribution representative of it. In the past, this could be a cumbersome task. Today there are software packages which are designed to automatically find standard probability distributions that are representative of empirical data. The use of these packages can substantially reduce the time required to perform this task.

8 STATISTICAL ANALYSES OF SIMULATION OUTPUT

Multiple and *independent* model replications are always required with stochastic simulations. The statistical analysis of the output generated by them is a prerequisite for making valid conclusions. Recall that probability distributions in conjunction with random numbers are used to create values representative of a system's stochastic behavior. The random numbers created are produced from an initial number (random number seed). Each number seed produces a unique stream of decimal random numbers (random numbers with values between 0 and 1). Decimal random numbers are translated to random values associated with a probability distribution. When number seeds are changed, a different set of random values are created.

Individual number seeds are assigned to each stochastic process. The results yielded from a single model replication are directly related to the number seeds selected. Changing the seed values will change the sequence of events occurring within a simulation. Data generated from stochastic simulations is itself stochastic. Output from multiple model replications must be analyzed with principles of statistical inference in order to make valid conclusions.

Making conclusions from a single model replication is like rolling a die once, and then concluding that the value rolled is the overall average value for any number of additional rolls. The results from a single replication of a stochastic simulation represent one possible outcome from an infinite number of possibilities. The output from a single and independent model replication is just one random sample from the unknown distribution of all possible outcomes. By obtaining "**n**" random samples (*multiple* and *independent* model replications) from the unknown distribution, we can make point estimates (designated as $\overline{\mathbf{x}}(\mathbf{n})$) of μ, the theoretical true mean of the unknown distribution. From the *Central Limit Theorem*, we assume that the distribution of all possible $\overline{\mathbf{x}}(\mathbf{n})$ is normally distributed. This allows us to apply basic statistical analyses to develop confidence intervals for point estimates of μ.

Most managers, engineers, designers, and financial personnel have at least one statistical course in their educational portfolio. However, the majority of us probably do not apply statistical theory in our daily routines. If decision makers do not understand the procedures used to analyze simulation results, then they will probably not feel confident with the recommendations presented to them. A little refresher course on basic statistical methodologies can be very beneficial for anyone involved with simulation. The concepts are not difficult to understand. It is usually just a matter of taking the time to review them.

An unfamiliarity with statistics should not discourage someone from using simulation. Most simulation packages contain features that will automatically perform basic statistical analyses on simulation output. The important thing is to have a fundamental knowledge of the various statistical analyses, and their purpose.

9 BUILDING A SUCCESSFUL SIMULATION MODEL

Formulate And Analyze The Problem

The first and utmost step in any simulation analysis is to define the objectives of the simulation. *Objectives* are one of the primary design factors in a simulation model. Model design cannot begin until objectives have been established. Objectives should be clearly stated and understood by management and all people involved with the simulation effort.

Assumptions are a common and required element in almost every type of analysis. Assumptions can simplify the building of a model, but they can also influence the results. It is better to start with many assumptions, and to reduce them at a point when deemed necessary. An assumption is good until it is discovered that it significantly impacts simulation results. When this occurs, it becomes obligatory to reevaluate the assumption.

Milestones, manpower requirements, and *responsibilities* must be defined for each task in the simulation analysis. In turn, management must be willing to commit the necessary resources to complete the tasks.

Educate The Team On Basic Simulation Methodologies

An important, yet often overlooked step in a simulation project is *training.* The simulation user (model builder) should obviously have a good comprehension of simulation methodologies and principles. What about the other people involved-managers, engineers, operational personnel and those who will be affected by the results of the analysis? Simulation has been around for a long time. However, there are many people who are not familiar with it. Educating project participants on simulation fundamentals can embellish findings, reduce project duration and make "selling" and implementing solutions much easier.

Develop Model Concept

Modeling strategy involves making decisions regarding how a system should be represented in terms of the capabilities and elements provided with a simulation package. The overall strategy should focus on finding a model concept that minimizes the simulation effort while ensuring that all objectives of the study are met.

The *level of detail* put into a model is dependent upon the availability of existing data and other information pertinent to a study. A model of a hypothetical system would have less detail than a model of an existing system. The primary focus should be on capturing the conditions and facts that can have a bearing on the objectives of a simulation.

Black boxes are used to represent elements in a system where adequate information regarding the operation of an element is not readily available, or feasible to obtain. Parts fabricated at an off-site vendor's facility is a good example. It would not be practicable to model a vendor's manufacturing facility. A black box approach is a better way to represent it. The only properties of a black box are something goes in and something comes out. What happens inside is not considered. The only concern is the amount of time spent in the box.

Collect Macro Data

Macro data is fundamental facts, information, and statistics derived through historical records, experience, or by calculation. It is acquired by taking a high level perspective of a system being modeled. Macro data is not concerned with particulars. Its purpose is to *1) provide a basis for establishing a model's input parameters and 2) to pinpoint input parameters which will require detailed (micro) data collection.*

Process flow charts are a good tool for determining system interrelationships and the rules that govern their dynamics. They sequentially reflect each step and procedure involved in a process. Questions regarding who, what, when, where, why, and how are correlated for each step. Elements whose performances are influenced or controlled by other elements are identified. Creating these charts forces a thorough examination of a process. The information acquired becomes the foundation and structure for building a model.

Model Concept & Macro Data Checkpoint

Prior to commencing the actual model building, it is important to review the macro data that has been collected. It will help ensure a concurrence on the findings. This is best accomplished with a group meeting attended by all involved parties (managers, decision makers, engineers, data contributors, and financial personnel). Inaccuracies can be discovered and corrected much faster through a "group" review of the data. It will help establish a *team* ownership in the model.

Construct The Model

Today's simulation packages make model building part science and part art. No two people will probably have the same modeling approach. There is never a single *right* way to model a system, but there are generally some approaches that are better than others.

A good guideline is to build a model in a piece by piece fashion. Each section should be functioning properly prior to starting the next. A continual interface with management, designers, and operational personnel is vital during the model building process.

Model Verification

The primary purpose of verification is to ascertain the correctness of a model's functional and computational proficiencies. Do the equations and instructions built into a model work as they were intended? Suppose a model element represents a machine that has a normal distribution with a mean time of forty minutes. The cycle time in the model for that machine is verified if the model produces cycle times representative of the normal distribution specified. Any data being sent to external data files needs to be checked to assure its format and correctness.

Another aim of model verification is to confirm a model's ability to generate output information that can be used to satisfy the objectives of a study. Perhaps an objective is to determine the impact of various lot sizes on product makespans. Do calculations performed by the model accurately compute statistics which are pertinent to evaluating the effect of lot sizes?

The verification process does not begin with the completion of building a model. It starts at the onset of a project and remains an on-going task throughout a project.

Test Model With Macro Data

The primary purpose of testing a model with macro data is to determine the input parameters and assumptions that exert the greatest influence on performance criteria. More detailed data may have to be collected for these factors in order to improve the model's ability to mimic the operational characteristics of the system being studied. The goal remains the same- add detail to a model only when it is necessary.

Valuable insight regarding cause-and-effect relationships between input parameters and performance criteria can be gained with the execution of this step. It helps the project team to focus on areas that will have the greatest impact on system performance. The potential consequence of by-passing this step is wasted hours investigating factors which have little or no influence on the objectives of a study.

Model Validation

Models often contain a large number of elements, numerous interrelationships, and many rules and logics that govern their interactions. They are typically constructed in a piece-by-piece manner, with each model segment being tested for validity before starting another. When all segments have been constructed, it is necessary to validate the aggregate behavior of the overall model when all model segments are working together.

It is probably fair to say that there are no models of *stochastic* and *dynamic* systems, simulation or otherwise, which will provide an exact and perfect imitation of the systems they are representing. Models are just approximations of actual systems. The purpose of model validation is to ensure a model's ability to respond in a manner that is consistent with the rationale and intellect associated with the system being studied. It assures that good judgment and common sense were used when constructing a model.

Model validation establishes credibility in a model. It is especially important for management and other decision makers to have confidence in the results that will be produced by a model. The validation process, like model verification, really begins at the onset of a project and perseveres throughout its entirety. Keeping the decision makers actively involved in the model building process will make model validation much simpler.

Design Experiments For Evaluating Experiments

Experimental design is the development of procedures and tests for analyzing and comparing alternatives. Its purpose is to maximize the usefulness of the information produced from simulation runs, while minimizing the effort. Without such a plan, it can be difficult to make an equitable comparison between candidate solutions.

The conditions that produce variability in simulations can be controlled. Stochastic drivers in an experiment can be kept the same for each alternative investigated. An identical sequence of events can be recreated for every experiment. Variance reduction techniques can then be applied to the test results in order to highlight the contrasts between alternatives. Numerous candidate solutions can be statistically analyzed to evaluate their performance with respect to selected criteria.

Put in simpler terms, experiments involving stochastics can be designed in a manner that will guarantee that each alternative tested is subjected to the same randomness.

Make Multiple Model Runs For Each Experiment
Multiple model replications are always required when stochastics are involved. A rule of thumb is to always perform at least three to five replications for each experiment. A more accurate point estimate is likely to be achieved as the number of replications increase. However, there is a point of diminishing returns where additional replications will not significantly improve the exactness of a point estimate. The cost of achieving a desired accuracy level has to be weighed against the cost of attaining it, and the benefits anticipated from it.

Statistical Analysis Of Output
The results obtained from independent model replications must be analyzed with principles of statistical inference. Warm-up periods, point estimates, and confidence intervals are determined for selected criterion.

Identify Best Solutions and Document The Results
Documentation can be divided into five areas: *1) Objectives and Assumptions, 2) Model Input Parameters, 3) Experimental Design, 4) Results, and 5) Conclusions.*

All *objectives and assumptions* should be recorded at the onset of any simulation project. Any changes or modifications made during the course of building a model need to be included in the final report.

An overview of the *model input parameters* contains a recap of the data used with a simulation. System flow charts, mathematical calculations, performance criteria, solution constraints, solution restrictions, and any cost related information should be included.

The *experimental design* section is comprised of descriptions regarding the alternatives investigated, the experiments designed for comparing alternatives, starting conditions, stopping conditions, a history of the random number streams employed with each experiment, and an account for the number of model replications performed for each alternative.

The *results* section is composed of the output data produced by a simulation. It also provides an overview of the statistical analyses performed on the data. Tables and graphical charts that illustrate the findings are very beneficial.

One of the final steps in any decision-making process is to make *conclusions and recommendations.* This demands that benefit-to-cost ratios be investigated for each alternative.

Presentation Of Results And Implementation
Presenting the results of a simulation study should be a team presentation. The results of the project reflect the collective efforts of the individuals responsible for the many aspects of the project. The project team and the *customers* of the simulation project should be in attendance. In today's "Total Quality Environments", "customers" are individuals that may have sponsored or funded the study, decision makers that will use the results of the simulation process, and possibly personnel that may be impacted by the projects results. This is also an excellent forum to expose other potential customers to the benefits of simulation.

Communication with the project team and customers is an on-going requirement during any successful simulation study. Thus, the presentation of results should not contain any surprises. The following items should be addressed with references to technical, operational, and financial concerns: *1) Restatement and confirmation of the project objectives, 2) What problem was solved, 3))Review of project methodology, 4) Benefits of the proposed solution,* and *5) Alternatives rejected and why.*

10 BUILDING A COST PERSPECTIVE INTO SIMULATIONS

Incorporating a cost perspective into simulations often provides a better means for evaluating candidate solutions. With simulation, problem-solvers experiment with alternative courses of action to find the most effective solution to the problem at hand. They must work within the bounds of a myriad of technical, operational and physical constraints.

In most organizations, the ultimate constraints or assumptions are the financial resources or available budget. To a simulation user, this means that potential solutions should be evaluated based on their highest dollar benefit to a company. A simulation user must present effective solutions that address not only operational, technical and physical objectives, but also the financial objectives of an organization.

The incorporation of a cost perspective into a simulation analysis can be facilitated by answering the following four questions: *1) What cost information is needed?, 2) Where can the cost information be obtained?, 3) How can cost information be processed and/or computed? and 4) How will the cost results be interpreted from the simulation?*

A simulation analysis should meet both the *operational* and *financial objectives* of a project. These are not independent tasks, but rather synergistic parallel tasks. For each step in the model building process, there is an associated financial corollary. A challenge is to find the most productive way to integrate the cost information associated with each step.

There is a range or *hierarchy of cost integration* for obtaining and processing cost information. At the higher end of the hierarchy, the optimal solution would have *concurrent* processing of cost and quantitative operational data fully within a simulation model. The lower end of the hierarchy, but still a workable process, would be the *external* processing of cost data from the simulation model e.g. spreadsheets. Select a method that will give you the desired level of cost information while minimizing the effort. Regardless of the method selected, the underlying goal is to add detail to a model only when it is deemed necessary!

11 ASSESSING SAVINGS FROM A SIMULATION INVESTMENT

Simulation is a tool that can enhance quality and improve performance, but these benefits must be translated to dollar savings using a logical methodology. The purchase of a simulation package is usually contingent upon a justification process. The profits anticipated must be greater than the cost of obtaining them.

The justification of a simulation investment is usually a double justification involving *1) the justification of a new problem-solving process or tool, and 2) the justification of a specific simulation product.* The investment in simulation usually consists of simulation software and a budget for initial consulting and training. Optionally, the investment may include some computer hardware, and on-going product software maintenance. Depending on the dollar value of the investment in relation to the company's capital and expense approval guidelines, there is usually a requirement that a capital appropriation request be prepared. This document should *1) analyze the potential investment with respect to alternatives,* and *2) show why the investment is a good business decision.*

The major steps that are included in a justification methodology are *1) Collect and 2) Process meaningful data for analysis 3) Evaluate the results,* and *4) Present justification results in a meaningful report.* To prepare an assessment of the savings from using simulation, it is necessary to identify the tasks and areas that will be *impacted* by simulation. Only those areas that experience a change in cost of required resources should be considered in the analysis. For analysis purposes, the simulation impacts can be classified as *1) Manpower;* and *2) Operations.* Both of these areas can be further categorized as: *1) Existing tasks which will be subject to productivity improvements, 2) Existing Tasks which will be avoided with simulation,* and *3) New and/or additional tasks or costs required due to simulation.*

The following seven *manpower* problem-solving tasks will generally be subject to productivity improvements necessitating fewer man-hours required to complete the task. *1) Problem Identification 2) Developing an analysis method, 3) Computer Programming, 4) Spreadsheet Analyses, 5) Opinion Modeling, 6) Trial* and *Error Experimentation, 7) Manual Calculations. Operations* cost savings can include the following items: *1) Computer Run Time, 2) Outside Consulting, 3) Better capacity planning, 4) Carrying Costs* and *Wait Time, 5) Lot Size Improvements.*

Financial factors can be included in a justification analysis, depending on the level of desired sophistication. Financial factors include *1) Impact of Interest Rates, 2) Impact of Taxes,* and *3) Impact of depreciation.* A consistent basis of evaluation is necessary to evaluate the impacts of simulation. Many organizations still rely on the more traditional common denominators of economic analysis such as the Internal Rate of Return, Payback period, and a cash flow analysis.

Often it will be the intangible benefits that influence the decision making process when tangible benefits between alternatives are substantially equivalent. As a minimum, intangible benefits should always be included in the narrative portion of a justification. Selected intangible benefits include: *1) Education-Simulation fosters a real need to thoroughly understand the process and/or problem which is the subject of the simulation. 2) Teamwork and Communication 3)More meaningful work,* and *4) More efficient use of problem solving time and dollars.*

For those situations where the problem-solving budget is fixed, simulation will often provide more horsepower per manpower dollar expended when compared to non-simulation methods.

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