10 Rules for Determining when Simulation is Not Appropriate

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Simulation modeling has become an essential tool for analyzing anticipated performance, validating designs, demonstrating and visualizing operations, testing hypotheses, and performing many other analyses. It is the preferred tool in a variety of industries and in some industries, it is even required prior to all major capital investments. In previous articles we have discussed the "how's" of simulation modeling—how to get started, how to select software, how to manage a successful project, and so on. The underlying assumption of these earlier articles is that simulation modeling is the correct tool for the problem that you are trying to solve.

A question that is often overlooked but should be asked is as follows: Is simulation modeling the right tool for the problem? This article discusses cases in which simulation modeling is inappropriate. In the past, simulation modeling was reserved for only very large or specialized projects that required one or more programmers or analysts with specialized training and much experience. The recent proliferation of simulation software has led to a significant increase in applications—many by users without appropriate training or experience. It has also lead to an increasing dependence on simulation to solve a variety of problems.

Although many of these projects are successful, the tool can be, and sometimes is, misapplied. We're concerned that this can lead to unsuccessful projects, and that simulation modeling, or the simulation software, may be mistakenly held at fault. An awareness of when quantitative problem requirements or when qualitative project dynamics indicate that simulation may not be appropriate should help avoid this mistake. In this article, we present some guidelines to consider before selecting the analysis tool for your next project.

Don't simulate when:

1) *The problem can be solved using "common sense analysis."* Consider the following example:

An automobile tag facility is being designed. Customers arrive at random to purchase their automobile tags at a rate of 100 per hour. The average time for a clerk to serve a customer is five minutes. What is the minimum number of clerks required? The utilization rate, r, is given by r=l/cm, where

l= arrival rate (100/hour)

μ= service rate (12/hour)

c = servers (the unknown quantity)

To avoid an explosive condition, $\rho < 1$. Thus,

Multiplying across gives $\lambda < C\mu$

Solving for c gives $c > \lambda/\mu$

So, $c > 100/12 = 8.33$

Thus, to avoid an explosive situation, at least nine clerks will be needed. The more clerks, the shorter the average waiting time. This problem could have been analyzed by simulation, but that is unnecessary, and would take longer to program and run than the above solution.

2) *The problem can be solved analytically (using a closed form).* There are steady state queuing models, probabilistic inventory models, and others that can be solved using equations—i.e., in a closed form—and this is a much less expensive method to use compared to simulation. This is called an M/M/c model where the first M indicates Markovian arrivals, the second M indicates Markovian servers, and c is the number of parallel servers. Markovian is another way of saying that the values are exponentially distributed.

An equation can be used to determine the probability that the system is empty, from which the average number in the system can be determined. A graph was developed by F.S. Hillier and G.J. Lieberman to accomplish the same result. Using that graph, the average number in the system, L, is 10.77. Little's equation relates L and w, the time in the system, as follows:

$L = \lambda w$

So, $w = L/\lambda = 10.77/100 = 0.1077$ hour

Customers spend their time either waiting in queue or being served. That is, $wq = w - 1/\mu$

where $1/\mu$ is just the average service time, or 1/12 hour. Then, $wq = 0.1077 - 0.0833 = 0.0244$ hour

This is certainly a much faster analysis than using simulation.

3) *It's easier to change or perform direct experiments on the real system.* This might seem obvious, but not always. We've seen cases where a model will be commissioned to solve a problem, and actually take more time and money to complete than a simple direct experiment would have required. Consider the case (a true story) where a detailed model of a drive-through, fast-food restaurant was constructed and used to test improvements on customer service time of adding a second

drive-up window. The model took weeks to complete. We observed a competitor test the same concept by staging a second person with a remote hand-held terminal and voice communication along the drive-up line. The competitor completed the entire study in a matter of days.

The rule of thumb here is: If the problem involves an existing system, which can be perturbed or measured without undue consequences, look first for a direct experiment to answer the questions. In addition, a direct experiment avoids all questions relating to whether the model was detailed enough or was properly validated, etc.

4) *The cost of the simulation exceeds possible savings.* Although almost every simulation project has many "qualitative" benefits, the expense of the model, data collection, and analysis is usually justified by the expected quantitative stake. Accurately estimating the total costs of a simulation project requires some experience. Factors to be considered include:

- Project planning, problem definition, and process documentation;
- Model development and testing;
- Data collection, review, and formatting;
- Model validation;
- Experimentation and analysis;
- Possible updates/enhancements to the model, retesting, etc; and
- Project documentation and presentations.

Also to be considered are costs of the simulation software (if not readily available) and computer resources. Simulation of a complex problem can easily run into the tens of thousands of dollars. Models of large facilities with complex operating procedures and control logic (such as a large distribution center), or the need to use real (historical) data or actual product location and quantities can raise the cost even higher. Generally, simulation project costs are compared to potential savings or cost avoidance. If the potential savings are not clearly greater than the estimated simulation costs, the model may not be justified. On the other hand, some simulation projects are undertaken because of perceived risk for systems that are too complex to understand otherwise. The model provides a level of insurance to understand if and where possible problems lurk. Can a price be calculated for this risk reduction?

5) *There aren't proper resources available for the project.* Primary resources required to complete a successful simulation project include people, software/computers, and money. The most critical component in any successful simulation project is people—experienced analysts who understand the problem, select the proper level of detail, translate it into a simulation model requirement, program the model, etc. It's hard not to agree with this statement, yet it's surprising how often we see attempts to solve important problems with simulation by a person with little or no training and without proper experience.

Simulation is both an art and a science, with the art gained through experience, and the science gained through proper training. The advanced simulation software now widely available certainly helps, but it's not a substitute for the proper human resources for a project. If a properly trained simulation modeler is not available for a project, it might be best (and less risky) to look for outside help. Remember that a poorly constructed model is worse than no model at all because the flawed results may be used anyway.

The next most critical resource for a project is funding. Assume that you are to manage a project, you have properly trained people, and you have the appropriate software, but the project cost estimate is twice the available project funding. How to proceed? Our recommendation is not to simulate. Most likely, the project objectives will have to be compromised, and corners will have to be cut in the model design and planned analysis experiments in order to come close to the budget. This will put the project goals at risk, because the resulting model may not be capable of providing the required results. Simulation, or the software selected, or both, will be mistakenly held at fault.

6) *There isn't enough time for the model results to be useful.* Another class of insufficient resources is time. This is usually caused by one of three reasons:

- The project schedule is too short;
- Model development and testing takes too long; or
- The window is too narrow.

This is a very frustrating, but not uncommon problem: You've worked hard to complete a model, carefully verified and validated it, and are in the middle of running experiments, when you're told that "the decision has already been made to proceed with the facility because we didn't have time to wait for the simulation results." Simulation studies tend to be commissioned at the last minute, many times as a final check. Often, the schedule is unrealistic to begin with. If there isn't sufficient time to conduct a proper project, the analyst must make coarser assumptions, skip details, or otherwise cut corners in an attempt to meet the schedule. How do you know if critical detail was left out and the results are not meaningful? No textbook can define where the level of detail should be set—this is based on experience, on a project-by-project basis.

Often, when we see a simulation project go beyond the estimated schedule, we can trace the blame to an inexperienced analyst working on the solution. A simulation model should be detailed enough that the questions posed can be answered, but not too detailed. A typical error for an inexperienced user is to start with too much detail, which invariably takes longer to develop and test than was initially estimated and scheduled. Remember one of the simulation maxims: If the results aren't used, the project may be regarded as a failure. It may be better if you don't use simulation if there's just not enough time allowed in the overall project schedule to produce results and put them to use. This means allowing time to change the system design and re-simulate if needed!

7) *There is no data—not even estimates.* During the design phase of a simulation project, one of the most critical tasks is to determine if the data required to meet project expectations and support the level of detail planned for the model is available, and if not, how it can be obtained. In some cases the data may not be available, and either impossible, impractical, or too expensive to collect. Don't fall into the trap of committing to a project and building the model before checking to see if the necessary data is available. The temptation will be to proceed with the analysis anyway, since you've already expended the effort to build the model, and people may be counting on the results. It is possible to perform sensitivity testing using estimates of the data values, but this still requires estimates about the range of values for critical data items!

8) *The model can't be verified or validated.* This problem is usually caused (again!) by lack of one of three critical ingredients: people, data, and time.

• The project analyst may not understand how to properly verify the model (lacks sufficient training and/or experience);

• You may not have useful performance data for comparing the model results against test scenarios in order to validate the model; or

• The project schedule doesn't allow for sufficient testing and/or validation activities.

The correct procedure is to first complete a base case scenario by comparing the model results against those for the real system (or expected of the real system), then use this case to compare future test cases. There are many other methods that can be used, even if we don't have data for the base case. A few of them are as follows:

• *The "degeneracy" test*—This test looks to see if the model behavior degenerates appropriately to extreme inputs. What happens when arrival rates get really high? How does the model respond? Do bottlenecks develop where expected?

• *The face validity test*—This test simply applies common sense to analyze model outputs for the base case. Is the output reasonable? Can we explain model behavior based on experience with similar systems?

• *The sensitivity analysis test*—For repeated test cases with different input values, do the outputs change in the direction anticipated? Do they all track together? These test procedures may help to build confidence in the model, but you must still question if it is sufficient to support the decisions that may be made based on simulation results. If the model is not properly verified and validated, results will be questioned and may not be accepted.

9) *Project expectations can't be met.* Nine times out of 10, the failure to meet project expectations is due to a failure to properly educate the decision makers about what is realistic and possible when solving the problem with a simulation model. Management may have unreasonable expectations—usually they expect too much too fast. When it can't be delivered, they may mistakenly blame simulation technology, or the analyst. Here's another version of the problem:

People with no experience in simulation often conclude that once a system is modeled, the model will be capable of answering any question that they ask of it. It can be difficult to explain, especially late in a project, that models are capable of answering only explicit questions that they were designed to address. In the remaining one of 10 times, the analyst overestimated either his own capability or the software's capability.

10) *The system behavior is too complex or can't be defined.* The system to be simulated must be thoroughly understood before simulating or the analyst will be forced to guess or be creative. Some systems are so complex that building an accurate model (within an acceptable schedule and budget) is not possible. This is often the case when human behavior is a critical part of the simulated system.

For example, because modern automated distribution centers are complex, they are frequently simulated prior to implementation or modification. Most are driven by computerized warehouse management system (WMS) software, which selects and combines orders to process. Almost all of the actual order processing (picking) is performed manually, and people run the facility, even in automated facilities. Typically, the scenario simulated is an average day, and the model results can be quite accurate. But in a real facility when an unusual event occurs and the orders start falling behind schedule, people will change their normal behavior or activities to find a way around the system constraints in an attempt to meet the schedule. This behavior can be quite varied and virtually impossible to completely describe and simulate for all possible scenarios. Model results for these crash-case scenarios almost never match what occurs in the real system, and simply are unreliable.

Conclusions

Simulation can be such a powerful analysis tool that it tends to be regarded in some industries as a universal solution. Every problem is not a nail with simulation as the hammer! Perhaps, in part, because of the variety of success stories in recent years (for otherwise intractable problems), or perhaps in part because of the ready availability of sophisticated simulation software packages claiming that anyone can use them, simulation is frequently the only tool considered. Not all of these projects have a successful conclusion. Simulation is often mistakenly blamed, when in fact it was just misapplied.

Simulation projects cost money, and can produce a significant return on investment when conducted properly. If the project is successful, then the money is well spent and will promote the technology. If the project is not successful, it hurts the reputation of simulation and, by association, each of us. Don't commit to a simulation project if there is no need or if there's a real chance that it can't be properly completed, can't meet the project goals and expectations, or the results won't be available in time to be used. Each analyst has a responsibility to make every project successful, to help continue the use and acceptance of simulation modeling.

For further reading

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