SIMULATION STUDIES OF TELECOMMUNICATION NETWORKS AND THEIR CREDIBILITY

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ABSTRACT

In telecommunication networks, as in many other areas of science and engineering, proliferation of computers as research tools has resulted in the adoption of computer simulation as the most commonly used paradigm of scientific investigations. This, together with a plethora of existing simulation languages and packages, has created a popular opinion that simulation is mainly an exercise in computer programming. In new computing environments programming can be minimised, or even fully replaced, by manipulation of icons (representing pre-built programming objects with basic functional blocks of simulated systems) on a computer monitor. One can say that we have witnessed another success of modern science and technology: an emergence of wonderful and powerful tools for exploring and predicting behaviour of such complex, stochastic dynamic systems as telecommunication networks.

But this enthusiasm is not shared by all researchers in this area. An opinion is spreading that one cannot rely on the majority of the published results on performance evaluation studies of telecommunication networks based on stochastic simulation, since they lack credibility, and the spread of this phenomenon is so wide that one can speak about a deep credibility crisis. In this paper, this claim is supported by the results of a survey of publications on telecommunication networks in recent proceedings of the INFOCOM (an annual IEEE International Conference on Computer Communications) and in the IEEE Transactions on Communications.

We also discuss the main issues that influence the credibility of simulation results, their perils and pitfalls, and formulate guidelines that, if observed, could help to assure a basic level of credibility of simulation studies of telecommunication networks.

1 Introduction

The last decade of the twentieth century will be remembered as a time when computers found their place in primary schools and in private homes, and became ordinary items of equipment on desks in offices and businesses. This is also a time when the computing paradigm has begun its drift from computer networks to network computing. There is enormous interest, both in industry and academia, in creating an AAA network, a world-wide computer network able to offer Any information service, accessible from Any place and at Any time. Before it happens, scientists and engineers will have to investigate many challenging problems of network technology, and evaluate their possible solutions. These research activities are certainly accelerated by achievements in the area of scientific computing, with various easy-to-use software packages specially designed for conducting performance evaluation studies of telecommunication networks.

In the area of telecommunication networks, as in many other area of science and engineering, proliferation of computers as research tools has resulted in wide adoption of computer simulation as a new paradigm of scientific investigation, in addition to two traditional ones: theoretical studies and experimentation. Various user-friendly simulation packages offer sophisticated graphical user interfaces, animation of simulated processes, etc. This has created a climate for spreading a popular opinion that simulation is mainly an exercise in computer programming. Further, this programming can be greatly simplified, since there is a plethora of simulation languages which reduce designing of simulation models of telecommunication networks to placing icons (representing basic functional blocks of networks) in appropriate locations on a computer monitor, and then initiating simulation by selecting an appropriate button from a menu bar.

One can say that we have witnessed another success of modern science and technology: an emergence of wonderful and powerful tools for exploring and predicting behaviour of such complex, stochastic dynamic systems as telecommunication networks. As a matter of fact, stochastic discrete-event simulation has already become a commonly used tool of scientists and engineers in this area, contributing to about 50% of all published research results; see Figure 1. The figure de-

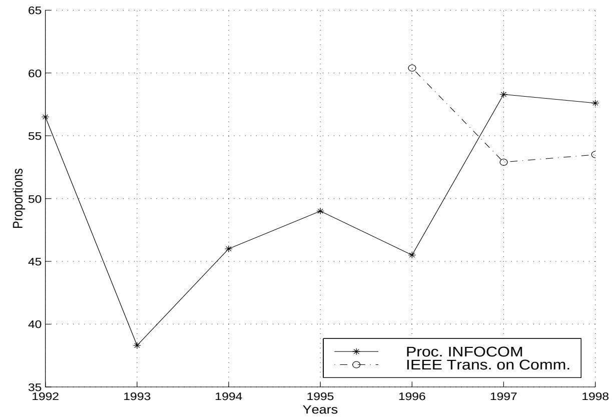


Figure 1: Proportion of all surveyed papers reporting results obtained by stochastic simulation

picts the data obtained from a survey of all papers published in proceedings of the INFOCOM (an annual IEEE International Conference on Computer Communications) between 1992 and 1998 (with the total number of papers per year ranging between 156 and 177 each), as well as in the IEEE Transactions on Communications between 1996 and 1998 (with the total of 230, 227 and 200 papers published, respectively, each year).

This enthusiasm is not shared by all simulation developers and users. A contrary opinion is spreading that stochastic simulation, as a performance evaluation tool of various dynamic systems, including telecommunication networks, is misused and that the spread of this phenomenon is so wide that one can speak about a deep credibility crisis. It is claimed that one cannot rely on the majority of the published results on performance evaluation studies of dynamic systems based on stochastic simulation, since they lack credibility.

In this paper we look at the motivation of such claims. We narrow our interest to the application of stochastic discrete-event simulation in performance evaluation studies of telecommunication networks, and discuss the main issues that can effect the credibility of simulation results, their perils and pitfalls, as well as formulate guidelines that, if observed, could help to achieve a basic level of credibility of simulation studies of telecommunication networks.

2 The issue of credibility

P. J. Kiviat in his opening address of the Summer Computer Simulation Conference SCSC'90 (Kiviat 1991) stated that "... *succeeding in simulation requires more than the ability to build useful models* ...". Some experts assess that modelling phase of a system for simulation consumes only 30-40% of the total effort in most successful simulation projects (Law and McComas 1991). The first necessary step of any performance evaluation studies based on stochastic simulation is to use a *valid simulation model*. In the case of telecommunication networks, it means a valid conceptual model of the network, based on appropriate assumptions about the network's internal mechanisms, limitations, stochastic characteristics of processes which will be simulated etc. A good discussion of general guidelines on how to build valid simulation models can be found for example in (Law and Kelton 1991). But this is only the first step for ensuring credibility of the final results of simulation studies.

The next step is to ensure that the valid simulation model is used in a *valid simulation experiment*. Two main issues, that have to be addressed when trying to ensure validity of any stochastic simulation-based experiment, are: (i) application of appropriate source(s) of randomness, and (ii) appropriate analysis of simulation output data. Let us look closer at these two issues.

Sources of randomness

It is generally accepted and commonly used practise today that algorithmic generators of (pseudo-random) uniformly distributed numbers are used as sources of basic randomness in stochastic simulation. The search for pseudo-random number generators (PRNGs), able to pass the most strict theoretical and practical requirements, has resulted in a number of good PRNGs, such as inversive congruential generators which do not exhibit lattice structures of n-dimensional random vectors (Leeb and Wegenkittl 1997), and the Mersenne Twister (Matsumoto and Nishimura 1998), a fast generator with the length of cycle equal $M = 2^{19937} - 1$ (!). The most popular PRNGs, multiplicative congruential generators with the modulus of $M = 2^{31} - 1$ have been exhaustive tested and a list of the best 10 of them (together with 404 slightly worse ones) in this class has been published in (Fishman and Moore 1986). Thus, there are many PRNGs of acceptable quality to choose from and to apply in standard simulation, on single processors.

This does not mean that all problems related with PRNGs have been solved. For example, there is a problem with use of uniformly distributed pseudo-random numbers from the same generator in distributed and/or parallel simulation, because of potential correlations existing between disjoint substreams of consecutive numbers (Entacher 1998; Hellekalek 1998). In such types of simulation one should use PRNGs with extreme caution. As A. Compagner, of the Technical University of Delft, the Netherlands, wrote : "... *results* <of stochastic simulation> *are misleading when correlations hidden in the random numbers and in the simulated system interfere constructively* ..." (Compagner 1995).

But, in the case of traditional, non-distributed and non-parallel simulation on single processors, one has to be careful too. Uncontrolled distribution of various computer programs has resulted in uncontrolled proliferation of really poor PRNGs, of clearly unsatisfactory or unknown quality. Thus, the advice given by D. E. Knuth of Stanford University in 1969 is even more important today, in the era of Internet: "... *replace the random generators by good ones. Try to avoid being shocked at what you find* ..." (Knuth 1969).

A longer list of useful practical guidelines on how to use, or do not use, PRNGs in simulation studies can be found for example in (Jain 1991), together with the advice that: ”... *it is better to use an established generator that has been tested thoroughly than to invent a new one ...*”.

Simulation output data analysis

Any stochastic computer simulation, in which random processes are simulated, has to be regarded as a (simulated) statistical experiment and, because of that, application of statistical methods of analysis of (random) simulation output data is mandatory. Otherwise, J. Kleijnen of the University of Tilburg, the Netherlands, warns that ”... *computer runs yield a mass of data but this mass may turn into a mess* <if the random nature of such output data is ignored, and then> ... *instead of an expensive simulation model, a toss of the coin had better be used”* (Kleijnen 1979).

Statistical error associated with the final result of any statistical experiment or, in other words, the degree of confidence in the accuracy of a given final (point) estimate, is commonly measured by the corresponding interval estimate, i.e. by the confidence interval (CI) expected to contain an unknown value, with the probability of this to happen known as the confidence level. In any correctly implemented simulation, the width of a CI will tend to shrink with the number of collected simulation output data, i.e. with the duration of simulation.

Two different scenarios for determining the duration of stochastic simulation exist. Traditionally, the length of simulation experiment was set as an input to simulation programs. In such *fixed-sample-size scenario*, where the duration of simulation is pre-determined either by the length of the total simulation time or by the number of collected output data, the magnitude of the final statistical error of results is a matter of luck. This is no longer an acceptable approach !

Modern methodology of stochastic simulation offers an attractive alternative solution, known as the *sequential scenario* of simulation or, simply, *sequential simulation*. Today, the sequential scenario is recognised as the only practical approach allowing control of the error of the final results of stochastic simulation, since ”... *no procedure in which the run length is fixed before the simulation begins can be relied upon to produce a confidence interval that covers the true steady-state mean with the desired probability level”* (Law and Kelton 1991). Sequential simulation follows a sequence of consecutive checkpoints at which the accuracy of estimates, conveniently measured by the *relative statistical error* (defined as the ratio of the half-width of a given CI and the point estimate), is assessed. The simulation is stopped at a checkpoint at that the relative error of estimates falls bellow an acceptable threshold.

There is no problem with running simulation sequentially if one is interested in performance of a simulated network within a well specified period of (simulated) time; for example for studying performance of a network during the first 24 hours of its operation. This is the so-called *terminating* or a *finite time horizon simulation*. In our example, one would simply need to repeat the simulation (of the 24 hours of network's operations) an appropriate number of times, using different, statistically independent sequences of pseudo-random numbers as basic source of randomness in different replications of the simulation. This ensures that the sample of collected output data (one data item per replication) can be regarded as representing independent and identically distributed random variables, and confidence intervals can be calculated using standard, well-known methods of statistics.

When one is interested in studying behaviour of networks in steady-state, then the scenario is more complicated. First, since steady-state is theoretically reachable by a network after infinitely long period of time, the problem lies in execution of *steady-state simulation* within a finite period of time. Various methods of approaching that problem, in the case of analysis of mean values, are discussed for example in (Bratley et al. 1983) and (Pawlikowski 1990). Each of them involves some approximations. Most of them (except the so-called method of regenerative cycles) require that data collected at the beginning of simulation, during initial warm-up periods, are not used to calculate steady-state estimates. If they are included in further analysis, they can cause a significant bias of the final results; see for example (Stacey et al. 1993). Determination of the lengths of warm-up periods can require quite elaborate statistical techniques (Goldsman et al. 1994). When this is done, one is left with a time series of (heavily) correlated data, and with the problem of estimation of confidence intervals for such data. But, although the search for robust techniques of output data analysis for steady state simulation continues (Pawlikowski et al. 1998), reasonably satisfactory implementations of basic procedures for calculating steady-state confidence intervals of, for example, mean values and quantiles have been already published; see for example (Pawlikowski 1990) and (Raatikainen 1990).

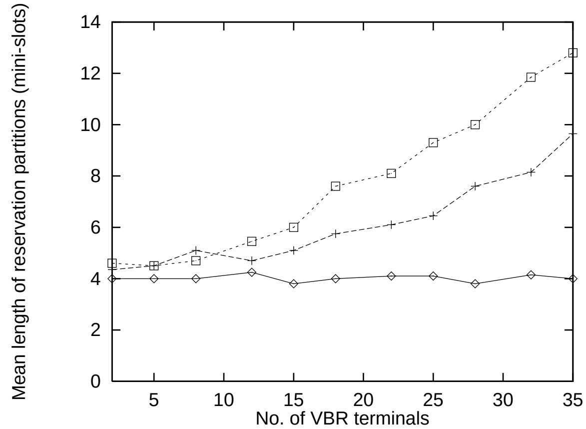
There are claims that sequential steady-state simulation, and the associated with it problem of analysis of statistical errors, can be avoided by running simulation experiments sufficiently long, to make any influence of the initial states of simulation negligible. While such *brute force approach* to stochastic steady-state simulation can sometimes lead to acceptable results (the author knows researchers who execute their network simulations for a week, or longer, to get the results, they claim, that represent steady-state behaviour of simulated networks), one can still finish with very statistically inaccurate results. It should be remembered that in stochastic discrete-event simulation collecting of sufficiently large sample of data is more important than simply running the simulation over a long period of time. For example, when analysing rare events, the time during that the simulated network is ”idle”, i.e. without recording any event of interest, has no influence on the statistical accuracy of the estimates of the event. What matters is the number of the events of interest recorded. This phenomenon is illustrated in Table 1, which shows that estimates of the mean delays of packets, obtained from a simulation of a DQDB network with 20 stations, over 1 500 000 time slots, can still be associated with as high relative error as 43%, or more (Lee 1991). The explanation, given in (Lee 1991), is clear: during this simulation many simulated time slots were idle. When there was no packet for transmission, no packet delay was measured, and no output data was collected.

station	traffic load		
	20%	60%	90%
1	0.090	0.048	0.101
2	0.059	0.047	0.090
3	0.103	0.055	0.120
4	0.131	0.057	0.101
5	0.110	0.038	0.137
6	0.131	0.049	0.128
7	0.109	0.080	0.084
8	0.069	0.056	0.119
9	0.081	0.080	0.108
10	0.135	0.076	0.157
11	0.208	0.062	0.172
12	0.186	0.091	0.212
13	0.226	0.091	0.145
14	0.314	0.143	0.106
15	*	0.102	0.202
16	*	0.145	0.203
17	*	0.211	0.243
18	*	0.248	0.430
19	*	*	*

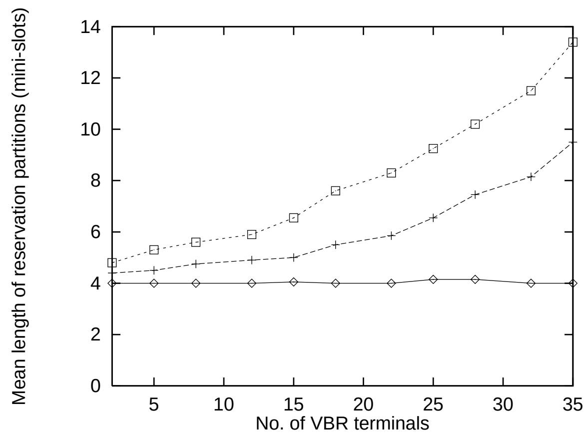
Table 1: Relative error of mean packets delays at stations of a DQDB network with 19 transmitting stations. All results obtained at 0.95 confidence level. The simulation lasted for 1 500 000 (simulated) time slots. Cases where the relative error were not assessed are marked by * (from (Lee 1991))

Obtaining final simulation results with small statistical error is especially important in comparative performance evaluation studies of alternative solutions. This phenomenon is illustrated by Figure 2, which shows the results of comparative analysis of three alternative versions of a reservation protocol for a wireless ATM network with integrated services (Rezvan 1998). The results were obtained by means of sequential simulation, continued until the relative error of the estimates became as small as 10% (in Figure 2.a), or as small as 5% (in Figure 2.b). One can see that results obtained with too large statistical error can be misleading or inconclusive. In this particular case, using the results with the error of 10%, one could erroneously conclude that two of three versions of the investigated protocol are equivalent as long as no more than 10-12 VBR terminals are used.

Unfortunately, sequential stochastic simulation is not very popular among designers of commercial simulation packages, with overwhelming majority of them allowing analysis of output data only after the simulation is finished. Such packages



(a) Results with statistical errors of 10% or less



(b) Results with statistical errors of 5% or less

Figure 2: Example showing influence of statistical errors on the final simulation results. Evaluation of three alternative versions of a reservation protocol for a wireless ATM network with integrated services; the assumed confidence level=0.95 (from (Rezvan 1998))

as, for example, SIMSCRIPT II.5[1], QNAP2[2] or Prophesy[3] are among the few exceptions. To this list of (commercial) packages able to execute stochastic simulation sequentially, one could also add a few packages designed at universities and offered as freeware for non-profit research organisations. One of such packages is Akaroa-2 (Ewing 1999), designed at the University of Canterbury, in Christchurch, New Zealand.

3 Crisis

It would be probably difficult to find a computer scientist or telecommunication engineer today who has not been trained

[1] A product of CACI, see http://www.caciasl.com
[2] From Simulog; see http://www.simulog.fr
[3] From Abstraction Software; see http://www.abstraction.com

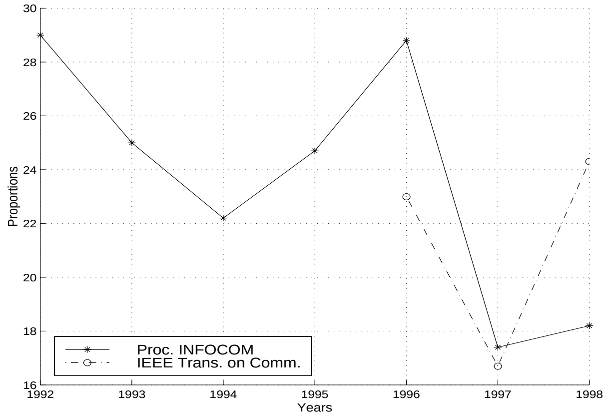


Figure 3: Proportion of all surveyed papers based on simulation in which results were statistically analysed

how to assess and minimise errors inevitably associated with statistical inference. Nevertheless, looking at further results of our survey of eight recent proceedings of the INFOCOM and three recent volumes of the IEEE Transactions on Communications, one can note, see Figure 3, that, on average, about 77% of authors of simulation-based papers on telecommunication networks were not concerned with the random nature of the results they obtained from their stochastic simulation studies and either reported purely random results or did not care to mention that their final results were outcomes of an appropriate statistical analysis. Let us add that Figure 3 was obtained assuming that even papers simply reporting average results (say, averaged over a number of replications), without any notion of statistical error, were increasing the tally of papers ”with statistically analysed results”.

While one can claim that the majority of researchers investigating performance of networks by stochastic simulation simply may not mention that their final results have been subjected to an appropriate statistical analysis, this is not an acceptable practise.

Probably everybody agrees that performance evaluation studies of telecommunication networks should be regarded as a scientific activity in which one tests hypotheses on how these complex systems would work if implemented, including even their possibly most critical conditions. But if this is a scientific activity, then one should follow the *scientific method*, generally accepted methodological principle of modern science (Popper 1968). This method says that *any scientific activity should be based on controlled and repeatable experiments.*

Through many repetitions of a non-sequential simulation one can eventually obtain the final results with acceptably small statistical errors. Thus, using non-sequential simulation it is still possible to control the error of final results. But, the real problem is that the vast majority of simulation experiments reported in telecommunication network literature is not repeatable. A typical paper contains very little or no information about how simulation was run. Our survey revealed that in almost 52% of papers reporting simulation-based results one would not find even if this was a terminating or steady-state simulation.

While the principles of the scientific method are generally observed by researchers in such natural sciences as biology, medicine or physics, this crisis of credibility of scientific outcomes is not limited to the area of telecommunication networks but has spanned over whole area of computer science, as well as electronic and computer engineering, despite of such early warnings like that in 1990, by B. Gaither, then the Editor-in-Chief of the ACM Performance Evaluation Review, who, being concerned about the way in which stochastic simulation was used, wrote that he was unaware of ”*... any other field of engineering or science* <other than computer science and engineering> *where similar liberties are taken with empirical data ...*” (Gaither 1990). What can be done to change the attitude of writers (who, of course, are also reviewers) of papers reporting simulation studies of telecommunication networks ? Consequences of drawing not fully correct, or false, conclusions about a network performance can be huge. On the other hand, thorough prediction of networks' performance could make such disasters as the 1990 failure of AT&T's entire long distance network avoidable. An interesting discussion of this type of dangers associated with modern computer and network technology can be found, for example, in (Lee 1992).

4 A Solution ?

The credibility crisis of simulation studies of telecommunication networks could be resolved if some obvious guidelines of reporting results of simulation studies were adopted.

First, the reported simulation experiments should be repeatable. This should mean that information about

- the PRNG(s) used during the simulation, and
- the type of simulation,

is provided.

In the case of terminating simulation, its time horizon would need to be specified, of course. The next step would be to specify

- the method of analysis of simulation output data, and
- the final statistical errors associated with the results.

High level of credibility of the final simulation results cannot be obtained without assessing their statistical errors, although sometimes, in preliminary studies, it can be acceptable to reduce the randomness of output results of simulation simply by repeating the simulation a number of times and averaging the results over replications. D. Knuth wrote that ”*... the most prudent policy for a person to follow is to run each Monte Carlo program* < or stochastic simulation of a telecommunication network> *at least twice, using quite different sources of pseudo-random numbers, before taking the answers of the program seriously.*”(Knuth 1969).

As mentioned, to achieve full credibility of a simulation one needs to develop valid simulation models and to use them in valid simulation experiments. The former includes accurate procedural representation of the simulated system's functionality as well as semantic and syntax correctness of simulation programs. The most effective way of achieving the latter is to use good, thoroughly tested PRNGs and to control statistical errors of simulation results by analysing them sequentially, i.e. to control the magnitude of statistical errors of results by stopping the simulation when the errors of the results reach a satisfactorily low level.

Negligence of proper statistical analysis of simulation output data cannot be justified by the fact that some stochastic simulation studies, in particular those aimed at evaluating simulated systems in their steady-state, might require sophisticated statistical techniques. On the other hand, it is true that in many cases of practical interest, appropriate statistical techniques have not been developed yet. But, if this is the case, then one should not pretend that he/she is executing a precise quantitative study of performance of a telecommunication network.

5 Final Comments

In this paper we have indicated the basic credibility issues of simulation studies of telecommunication networks, by looking at them as at computer-simulated statistical experiments. The results of a survey of recent research publications in this area of science and engineering suggest that the majority of recently published results of simulation studies of telecommunication networks do not satisfy basic criteria of credibility.

Of course, simulations of telecommunication networks are often computationally intensive and can require long runs in order to obtain results at a desired level of precision. Excessive runtimes hinder development and validation of simulation models. Research on speeding up execution of simulation of telecommunication networks is one of challenging problems which has attracted a considerable scientific interest and effort.

One direction of research activities in this area has been focused on developing methods for concurrent execution of loosely-coupled parts of large simulation models on multiprocessor computers, or multiple computers of a network. Sophisticated techniques have been proposed to solve this and related problems, surveyed for example in (Fujimoto 1990; Nicol and Fujimoto 1994; Bagrodia 1996). In addition to efficiently managing the execution of large partitioned simulation models, this approach can also offer reasonable speedup of simulation, provided that a given simulation model is sufficiently decomposable. Unfortunately, this feature is not frequently observed in practice, thus the efficiency of this kind of distributed simulation is strongly model-dependent (Wagner and Lazowska 1989).

In the context of stochastic simulation, there is yet another (additional) solution possible for speeding up such simulation. Namely, collecting of sufficient output data for their sequential analysis can be speeded up if the data are produced in parallel, by multiple simulation engines running statistically identical simulation processes. This approach to distributed stochastic simulation is known as Multiple Replications In Parallel (MRIP) (Pawlikowski et al. 1994).

Several research projects around the world, including project EcliPse (Rego and Sundram 1992) at Purdue University in West Lafayette, USA, and project Akaroa (Yau and Pawlikowski 1993; Ewing et al. 1999) at the University of Canterbury, in Christchurch, New Zealand, have been developing simulation methodologies able to fully use the enormous distributed power of modern computer networks. There are many challenging issues, and there is noticeable progress in this area.

One can expect that the credibility problem of practical applications of simulation will be overcome soon. An adoption of the basic guidelines indicated in this paper could be the first step in this direction. As stated at the beginning of this paper, the last decade of the twentieth century will be remembered as a time when computers found their place in primary schools and in private homes, and became ordinary items of equipment on desks in offices and businesses. Will this decade be also remembered as the time when the network research community abandoned the principles of the scientific method ?

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