Ultra Scientist Vol. 28(3)A, 141-144 (2016). ISSN 2231-3478 (Print)
www.ultrascientist.org 2319-8052 (Online)

# Modeling and Analysis of Stochastic Discrete Event Simulation of Communication Networks

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(Acceptance Date15th July, 2016)

## Abstract

In this paper,the study of simulation of communication networks. We present the simulation techniques typically used to solve a model of communication network or protocol is stochastic discrete event simulation. In discrete event simulation, various components of the actual network under study (e.g. the communication links, butters, access strategies network control structures) are represented within a computer program.

*Key words:* communication networks, discrete event simulation, queueing network.

## 1.1. Introducation

The trade offs between an analytic and a simulation approach toward modeling are in the relative amounts of time spent on model formulation and model solution. Since analytic models require a higher degree of abstraction, Consider able effort and skill may be required on the part of the network modular to develop a performance model that accurately reflects the system under study. In a simulation approach, the system may be modeled to any arbitrary degree of details the process model formulation thus becomes a more straight forward task, althoughit remains advantageous from a solution stand point to abstract out as many secondary system detail as possible. The solution of a simulation model requires significantly more computer time. In some cases, however,simulation is the only viable approach.

The simulation technique typically used to solve a model of a communication network or protocol is stochastic discrete event simulation.

### *1.2. The Statistical Nature of a Simulation Models :*

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The generation of events by the Simulation on program is driven by a stream of pseudorandom numbers. These random numbers might be used,for example to generate the lengths of messages, interarrival times of messages at a given node, time between failures of a link, or probability of a transmission error. Since the event generation process depends on the Pseudorandom number stream, the performance measures output by the model (e.g. queueing delay, device utilizations, butter occupancies, message loss, etc.) are themselves random in nature.

A simulation thus represents a statistical experiment and the performance results should thus be subjected to careful Statistical analysis. If the simulation had been run for either more of less time, or if a different stream of random numbers had been used, different values would have been obtained for these performance measures.

*1.3. Sensitivity Analysis of Simulation :*

An important part of any modeling study is that of sensitivity analysis determining how changes in model parameters affects system performance for example, a network modeler might be interested in the effect of an increased arrival rate or a decreased channel capacity on the average message delay. Sensitivity analysis also helps identity both critical model parameters, as well as those that have relatively little influence on performance. It thus also provides an indication of the quality and general validity of the model. If performance is extremely sensitive to a certain parameter value, the model may not be applicable over a wide range of parameter value.

The most straightforward, approach toward sensitivity analysis is to first run the simulation to determine the baseline performance for the given parameter values. The simulation is then run again several times, each time with a slightly performed value of a single model parameter clearly, if there are a large number of parameters, This can be a very costly process- if there are N parameters, the simulation must be run N times to determine model sensitivity for the baseline parameter values.

Recently, two approaches have emerged for estimating such sensitivity for gradient information from a single run of a simulation. Although their applicability is often restricted to certain classes of models or simulation techniques, they often a premising methodology for efficiently obtaining sensitivity information. The first approach is known as perturbation analysis [HO83].

A second approach for obtaining sensitivity estimates from a single simulation run is bases on the use of likelihood ration REIM[8] This techniques, which requires only that the occurrence of certain events be counted during the simulation, utilizes the natural variation in the random process underlying the parameter of interest to generate the sensitivity estimate.

As discussed above, sensitivity estimates provide important information about the robustness of the simulation results. An additional use of these estimates is in the automated Monte Carlo optimization of the network designs. Typically network performance results from a complex intraction among many parameters, or design variable and an explicity closed form expression seldom exists for the performance measures of interest, much less their derivatives. In such cases, one possible approach is to use simulation to optimize system performance with respect to the design variables. In this case the system is simulated of sensitivities with respect to the design variables are determined and the model parameters are them changed in the direction for which the performance increase is greatest. The system is then simulated again and this interactive process repeated until the design has been optimized.

*1.4. Speeding Up a Simulation:*

The major disadvantage as a simulation (as opposed to analytic) approach toward network performance modeling is the amount of time needed to simulate a model. Generally, as network protocols become more sophisticated and complex, so too do their performance models.

*1.4.1. Distributed and Parallel Simulations:*

One approach toward decreasing the amount of time needed to perform a simulation study is to distribute the computational burden of simulation among several processors in a distributed or parallel multiprocessor system [CHAN79]. In this approach, the simulation is partitioned into numerous logical processes, each of which is responsible for simulating one or more of the physical processes in the system being modeled. In a multiprocessor environment, different logical processes may be executed in paralled on the different processors, with the goal of decreasing the time required until the simulation is completed. Of course, processes may not proceed completely asynchronously, since causal interactions between processes in the physical system must also be maintained between the logical processes of the simulation. The manner in which this synchronization is maintained in the simulated system is of fundamental importance, Since it is this which prevents a K-fold speedup from being obtained when a simulation is distributed over K processors. An alternative to distributing a single simulation over K processors is to run K independent copies of the simulation in parallel, one on each of one K processors. In this case, no synchronization is required among the K processors.An alternative to distributing a single simulation over K processors is to run K independent copies of the simulation in parallel,one on each of the K processors.In this case, no synchronization is required among the K processors. At the end of the simulation the results of the K simulations are averaged and the statistical significance of these results determined. The simulation termination criteria must be carefully chosen in order to avoid introducing sampling bias into the estimates of the performance measures. A model is also developed for comparing distributing a single simulation over K processors with running K independent copies of simulation on K processors. The purpose of this comparison is to determine which approach is statistically more efficient *i.e.*, produce performance estimates with smaller mean squard error for the same amount of computing resources. It is shown that if the run length is long or the initial transient period is short, replicating a simulation is statistically more efficient than distributing a simulation.

*1.4.2. Hierarchical Decomposition and Hybrid Techniques :*

Hierarchical decomposition is a modeling technique for speeding up a simulation. In this approach, portions of the model are grouped into submodels and each submodelis replaced by a single composite queue with a queue length dependent service rate.

The potential speedup results from the fact that the submodel need one be solved once (for each possible customer population) in order to determine the service rates of the composite queue. Then, in the simulation of the entire model the potentially large number of events that would have occurred when a customer passed through the sub model are replaced by only two events. The arrival and eventual departure of the customer from the composite queue. Experimental results of decomposing extended queueing network models are reported and several rules of thumb are given for cases in which decomposition would be advantageous.

Note that the submodel itself may be solved either through simulation or analysis, even if the overall model requires a simulation solution. The possibility of such a hybrid approach toward modeling *i.e.*, combining both analysis and simulation in a single model, may result in even further reduction in model solution time.

*1.4.3. Variance Reduction :*

A third method for decreasing one run time of a simulation is the use of variance reduction techniques. These techniques exploit known statistical properties of the system being modeled in order to reduce the amount of time needed to obtain performance estimates of a given accuracy. An overview of the application of variance reduction techniques in computer network models. A promising recent variance reduction technique that has been applied to the simulation of queueing networks is based on the theory of large deviations.

## 1.5. Conclusion

In this paper, we have studied simulation of communication networks. The simulation technique typically used to solve a model of a communication network or protocol is stochastic discrete event simulation. In this approach, portions of the model are grouped into submodels and each submodels is replaced by a single composite queue with a queue length dependent service rate.

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