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An Analysis of the Applications of Monte Carlo Simulation in Various Disciplines

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Abstract— Monte Carlo Simulation is a helpful technology for analyzing and modeling real world situations an systems. Several quantitative issues in engineering, economics and science are solved through statistical sampling on computer nowadays. Such methods of Monte Carlo can be used in 3 various manners: 1) to calculate numerical quantities by repeated sampling; 2) to produce random processes and objects to examine their behavior; and 3) to resolve complex issues of optimization through randomized algorithms. The notion of using computers to perform statistical sampling dates back to starting of e-computing. John Von Neumann and Stanislav Ulam pioneered this process with the target to study the applications of Monte Carlo Simulation. This research explores an overview of Monte Carlo simulation and about the applications of Monte Carlo Simulation.

Index Terms— Monte Carlo Simulation, Applications of MC Simulation.

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I. INTRODUCTION TO MONTE CARLO

According to Rubinstein (1981) the phrase Monte Carlo in the method name represents that there is some stochastic component in it. Stochastic processes are proper clearly for the explanation of stochastic methods but it can be helpful to change a deterministic issue by a similar stochastic issue. The major notion of Monte Carlo processes is to indicate the mathematical problem solution by a parameter of a hypothetical or true distribution and to calculate that parameter value by sampling from this distribution. This notion offers a direct tie to coordinate the concept introduced into statistical mechanics by Gibbs and the wave function probabilistic interpretation in quantum mechanics. Similarly Raeside (1976) has mentioned that Once the physical system wave function is known the expected values can be expected by framing samples from the associated density of probability. This quantum Monte Carlo process is interesting because it offers a practical abstract conceptual interpretation of a wave function. Unfortunately the functions of wave are known only for a very reduced number of systems. There are numerous methods of Monte Carlo which gains the critical aim of simultaneously creating and sampling from the distribution of priori unknown quantum.

Fishman (1996) has described that in statistical physics Monte Carlo processes plays an essential role and have led to a greater technical standard of methods and algorithms to quantify statistical and systematic mistakes.The core notion of Monte Carlo Simulation is to use parameters of random samples or inputs to describe the complex process or system behavior. The scientists faced issues in physics such as neutral diffusion models that were too critical for an analytical solution so they had to be estimated numerically. They had access to one of the former computers MANIAC but their models consist of several dimensions that exhaustice numerical estimation was normally slow. Conversly Rosenthal (2000) has described that Monte Carlo Simulation assured to be effective at predicting solutions to these issues. Since the earlier time Montee Carlo proceses have been applied to a wide range of issues in engineering, finance and science and in business application in every industry. One applicable characteristic of Monte Carlo is that it is available to calculate the magnitude order of statistical mistake which is the dominant mistake in several computations of Monte Carlo. These calculations are always referred to as mistake bars because of the way they are represented on plots of Monte Carlo outputs. The mistake bars of Monte Carlo are significantly intervals of statistical confidence. The practitioners of Monte Carlo are among the avid customers of statistical analysis technologies. Monte Carlo’s another characteristic that makes academics happy is that easy clever ideas can lead to wide practical developments in accuracy and efficiency.

II. BASIC MONTE CARLO SIMULATION

According to Asmussen and Glynn (2007) the basic notion of Monte Carlo is very easy. Since the stochastic variables mean values can be represented as the variable's integral times the function of probability density the researcher can reverse the method by producing stochastic numbers and calculating their mean by easy averaging. In this the theory must give the researcher an approximation to integral.

Suppose the researcher has an integral to estimate of the form

$$I = \int_{\mathcal{D}} h(\boldsymbol{x}) f(\boldsymbol{x}) d\boldsymbol{x} \tag{1}$$

Where *D* is some domain with x and *f (x)* is a nonnegative function which fulfills

$$\int_{\mathcal{D}} f(\boldsymbol{x}) d\boldsymbol{x} = 1. \tag{2}$$

Equation (2) combined with the conditions of non negativity permits the researcher to interpret *f* as a function of probability density on *D.* Within this interpretation the equation (1) is just the expectation value formula of h(x) where x are random variables on D domain with pdf P (x) = f (x).

Kalos and Whitlock (1986) have described that if the researcher could produce *N* random variables x_i i.e. coordinates of vector with pdf P (x) = f (x) the I can be approximated in equation (1) by the experimentally examined average:

$$I = < h(\boldsymbol{x}) > \approx \frac{1}{N} \sum_{k=1}^{N} h(\boldsymbol{x}_k). \tag{3}$$

Even better the researcher can calculate the approximation standard deviation to I and get some mistake calculations as well.

The instance which the researcher explained earlier estimating the unit circle area can be in the form of cast. *D* is to square *x* [*x,y*] = [-1 1] × [-1 1]. *f (x,y)* = ¼ inside *D*, 0 elsewhere i.e. an even distribution and

$$h(x,y) = \quad 1 \text{ if } x^2 + y^2 < 1 \tag{4}$$

$$0 \text{ otherwise.} \tag{5}$$

In this case it is simple to produce sample xk of pdf *f* (*x*) and the integral *I* must estimate to π/4.

As big as the researcher performs in more than two dimensions the Monte Carlo process is ineffective and good approximations of numneric are possible to estimate *I* the integral. Such processes also sample *D* the space by discrete samples x_k, k = 1, …….*N*, but normally not in a random manner (Kloeden and Platen, 1992). For such processes in an M dimensional space *D* the approximation error reduces with N according to

$$N^{-1/M}, \tag{6}$$

Which is slow in greater dimensions. On the other side in the Monte Carlo process the mistake as

$$N^{-1/2}, \tag{7}$$

Khan,Kennedy and Chan (2005) have described that several scientific issues can be cast into the form (1). Normally *h* (*x*) is a critical and known function but f (x) can be estimated only with big effort as it consists of comprehensive simulation. The critical section of the Monte Carlo Simulation depends in predicting methods to produce random variables x that is scattered with pdf *P* (*x*) = *f (x).*

Around this one way would be to recast (1) into a varied form by referring

$$\hat{h}(\boldsymbol{x}) = V h(\boldsymbol{x}) f(\boldsymbol{x}) \tag{8a}$$

$$\hat{f}(\boldsymbol{x}) = 1/V, \text{ with} \tag{8b}$$

$$V = \int_{\mathcal{D}} d\boldsymbol{x}. \tag{8c}$$

The integral (I) views like in terms of these new hated functions:

$$I = \int_{\mathcal{D}} \hat{h}(\boldsymbol{x}) \hat{f}(\boldsymbol{x}) d\boldsymbol{x}, \tag{9}$$

and at least for D the hypocubical domains it is simple to produce sample x_k as f is the even distribution. Unfortunately this refers that if f was little on big regions in D the researcher is producing numerous samples x where it does not contribute most of the sample to average (2), This is wasteful because researcher's new *h* is costly to estimate since they have to estimate *f* each time which was costly. For big issues this is so worse that the process is too slow to be helpful in experiments.

III. WORKING OF MONTE CARLO SIMULATION

Kroese, Taimre and Botev (2011) have mentioned that Monte Carlo Simulation performs analysis of risk by enhancing available results models by putting an extent of values i.e. a probability distribution for any factor that has core uncertainty. Then it estimates outcomes over and over every time using a varied series of random values of the functions of probability. Relying upon several ranges and uncertainties specified for them a Monte Carlo Simulation consists of 1000s or 10s of re-estimations before it is finished. The Monte Carlo Simulation generates distributions of available values of outcomes. By using the distributions of probability the variables can have varied probabilities of various results existing. The distributions of probability are a much more realistic way of explaining uncertainty in risk analysis variables. Similar distributions of probability consist of:

Lognormal:

Values are skewed positively and it is not symmetric like an actual distribution. It is used to indicate values which do not reduce below 0 but have unlimited positive significance. Some of the instances of variables explained by distributions of lognormal consists of stock costs, oil reserves and values of real estate property (Kushner and Yin, 2003).

Normal:

According to Sheng, Guerrieri and Sangiovanni-Vincentelli (1991) It is also referred to as a bell curve. The user is referred the expected or mean value and a standard deviation to explain the difference about the mean. In the middle the values near the mean are most probable to exist. It is symmetric and explains numerous natural phenomena such as height of people. Some of the instances of variables explained by normal distributions consists of energy costs and rates of inflation.

Triangular:

The user refers the most probable, maximum and minimum values. Values near the most probably are likely to exist. Variables that could be explained by a triangular distribution consists of a history of past sales per time unit and levels of inventory (L'Ecuyer, 1999).

Uniform:

Entire values have an even opportunity of existing and the user normally refers the maximum and minimum. Some of the instances of variables that could be distributed evenly consist of future revenues of sales or costs of manufacturing for a new product.

Discrete:

L'Ecuyer and Simard (2007) have described that the user is referred particular values that may exist and the likelihood of each. An instance will be the outcomes of a lawsuit 30 percent chance of negative verdict, 20 percent chance of positive verdict, 10 percent chance of mistrial and 40 percent chance of settlement.

PERT:

Metropolis (1987) has mentioned that the user refers the most probably, maximum and minimum values similar to triangular distribution. Around the most probably the values are more probable to exist. However values between the extremes and most probable are more likely to exist than the triangular i.e. the extremes are not as accentuated. An instance of the PERT distribution usage is to explain the task duration in a model of project management. The values are sampled at random during a Monte Carlo Simulation from the distributions of input probability. Every series of samples is known as an iteration and the resulting output from that sample is recorded. Monte Carlo Simulation does this 100s or 100s of times and the output is a probability distribution of possible results. In this manner the Monte Carlo Simulation offers a more extensive view of what may occur.

IV. APPLICATIONS OF MONTE CARLO SIMULATION:

Monte Carlo simulation has been successful in many fields similar to modeling critical systems in engineering, geophysics, biological research, computer applications, meteorology,finance and in applications of public health studies.

Biochemistry and Biology:

Monte Carlo simulation has been used vastly in Biochemistry and biology to model the activity of molecules. Berney and Danuser (2003) explained their Monte Carlo simulation usage when modeling the technology of FRET (fluorescence resonance energy transfer) which measures the communications between 2 molecules. LeBlanc et al (2003) explained the Monte Carlo simulations usage of molecular systems corresponding to complicate energetic landscapes, and provided a new concept to develop these simulations convergences.

Other Monte Carlo simulation area usage common to biology are in evolutionary and genetics field studies. Korol et al (1998) used Monte Carlo simulation in genetics to describe the benefits of multi-trait analysis in discovery of connected effects of quantitative trait. In the evolutionary studies field one challenge is the Tree of Life assembly i.e.

an extensive phylogenetic tree used to understand the evolutionary methods better. To rebuild big tress such as Tree of Life with parameters concluded from 4 big angiosperm DNA matrices Salamin et al (2005) has used Monte Carlo simulation which could assist researchers radically in creating this tree.

Engineering:

Bhanot et al (2005) explained the simulation usage in the computer design and engineering field when optimizing the IBM ' s Blue Gene ® / L supercomputer problem layout. The analysis of Monte Carlo in geophysical engineering analysis has been used to find th stability of slope given different factors (El-Ramly, Morgenstern and Cruden, 2002). Santos and Guedes Soares (2005) explained a probabilistic methodology in marine engineering in which they have improved to assess spoiled survivability of ships based on the simulation of Monte Carlo. In aerospace engineering Lei et al (1999) described their Monte Carlo simulation usage to model the whole spacecraft and its payload geometrically using The Integral Mass Model.

Computer Graphics:

According to Shirley, Edwards and Boulos (2008) some applications of computer graphics such as the design of an architecture produces computer models realistic images visually. This is performed by either implicitly or explicitly resolving the equations of light transport. Precise solutions consist of Monte Carlo technologies and high dimensional equations are used with an emphasis on significance stratification rather than sampling. For numerous applications accurate solutions are sufficient and the problem's dimensionality can be limited. In these cases the sample distribution is essential and quasi Monte Carlo processes are always used. Still it is unknown what schemes of sampling are better for these lesser dimensional graphic issues or what better even refers in this case.

Business and Finance:

Glasserman (2004) has described that in Finance Monte Carlo processes are always used to estimate the company's value to estimate project investments at a corporate level or business unit or to estimate financial derivatives. They can be used to model the schedules of a project where simulations assemble calculations for the best case, most probable and for bad case durations for every task to decide results for the entire project. Monte Carlo simulation may be applied in time management to project schedules to determine the confidence project manager must have in completion date of target project or duration of the entire project allots the function of the probability distribution of duration to every group of tasks or tasks in the network of project to get good calculation. Similarly Robert and Casella (2004) have described that a 3 point calculation is always used to facilitate this practice, where the expert delivers the best case, most-probable and bad case durations for every group of tasks or tasks. Then the project manager can apply these 3 calculations to a distribution of duration probability such as a triangular distribution or normal, Beta for the task. The project manager is able to report the probability of finishing the project on any specific date once the simulation is finished which permits her or him to establish a schedule reserve for the project. The above can be finished easily using the software of standard project management such as Primavera or Microsoft Project along with add ins of Monte Carlo simulation such as @Risk or Risk.

According to Rubinstein and Kroese (2007) the project manager can use Monte Carlo simulation in cost management to perceive budget of the project better and calculate the last budget at completion. Instead of allotting a probability distribution to the durations of project task, the project manager allots the project's cost distribution. These calculations are usually generated by an expert of project cost and the last product is the probability distribution of the last cost of the project. Always the project managers use this distribution to place a budget reserve aside a project to be used when the schedules of contingency are essential to respond to events of risk.

Construction:

In construction projects also the Monte Carlo simulation has been used to perceive specific risks to the project better. For instance, detrimental effects of noise on the community environment is a risk in numerous projects of urban construction. Gilchrist et al (2003) has enhanced a model of Monte Carlo simulation that permits contractors of construction to find and solve the influence and existence of the noise of construction on their projects.

Telecommunications:

Hayes and Ganesh Babu (2004) have mentioned that the Monte Carlo Simulation is the most prominent in telecommunication systems. As the term represents the basis of this technique is the repeated probabilistic trials. There are exogenous input random variables that compete such occurrences as transmission times and arrival of random message. The system response samples to these inputs are taken and system performance calculations are estimated from these samples. For forming calculations of such capacities standard technologies as mean response time are used. Monte Carlo simulation of a telecommunication system becomes unfeasible quickly when the network attains a reasonable size. Similarly Jeruchim (1994) has described that to this problem the solution is a hybrid simulation both analytic models and Monte Carlo analysis are used to decide the network performance. For a precise analysis Monte Carlo Simulation still required foreground traffic and the background traffic behavior in the network tools can be explained analytically. The design must be assured to perform for a vast number of scenarios when planning a wireless network that rely mainly on several users, their places and services which they need to use. The processes of Monte Carlo methods are used to produce these users' states. Then the performance of the network estimated and, if outcomes are not fulfilled the design of the network goes through the process of an optimization.

Other Application areas:

Monte Carlo simulation is used to model the systems of weather and their outcomes in meteorology. For example, Gebremichael et al (2003) has used the analysis of Monte Carlo to estimate the uncertainty of sampling for choosing rain gauge networks in the GPCP (Global Precipitation Climatology Project). The Simulation has been used to evaluate the direct costs of avoiding Type 1 diabetes using nasal insulin in public health if it was to be used as a section of routine system of health care (Hahl et al, 2003). Phillips (2001) argued that Monte Carlo simulation must be used by research companies to decide whether or not future available research is valuable really the effort and cost, by modeling available results of the research. In personal financial planning Boinske (2003) used Monte Carlo simulation when evaluating how much cash one requires for retirement and how much an individual can invest annually once the retirement has started.

V. CONCLUSION:

Monte Carlo Simulation is a very helpful mathematical technology for identifying uncertain scenarios and offering a probabilistic examination of various circumstances. For applying Monte Carlo the basic principle is easy and simple to grasp. Different software has developed the adoption of Monte Carlo Simulation in various areas such as engineering, finance and business, computer graphics, telecommunications, biology, etc. Monte Carlo simulation offers one of the most helpful generic concepts to statistical computing. Essential advancements have taken place in the theory and application of Monte Carlo during the past few years. In this study the researcher has discussed the Monte Carlo Simulation, Working of Monte Carlo Simulation and Application areas of Monte Carlo Simulation.

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