كلية الحاسبات والذكاء الإصطناعي
Faculty of Computers & Artificial Intelligence

جامعة حلوان
HELWAN UNIVERSITY

الغلاف الخارجى للبحث

أولاً: البيانات الخاصة بالطالب			
الفرقة الدراسية	الثانية	التخصص	عام
اسم القسم	عام		
اسم المقرر	نمذجة ومحاكاة – Modeling and Simulation		
استاذ المقرر	د/ مي الضفراوي – Dr/ Mai El Defrawi		
ثانياً: البيانات الخاصة بالبحث			
عنوان البحث	Monte Carlo Simulation		
طبيعة المشاركة	بحث فردى	***	بحث جماعى
ارسال البحث	بواسطة البريد الالكتروني		

اسماء الطلاب المشاركين فى البحث (يكتب الاسم رباعيا)	م	الاسم رباعى	رقم الجلوس	الرقم القومى
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تاريخ الإرسال	7 / 6 / 2020			

ثالثاً: البيانات الخاصة بالكونترول				
النتيجة	ناجح		راسب	

أعضاء لجنة تقييم البحث		الاسماء	التوقيع
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فى حالة عدم قبول البحث يرجى ذكر الأسباب	
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Introduction:

Risk analyzes are part of every decision that we make. Uncertainty, ambiguity and variability are constantly before us. And while we do have unprecedented access to information, we cannot predict the future accurately. For this reason, a simulation is made to facilitate the analysis; takes the required data and makes an approach to the possible output. One of those simulations is the Monte Carlo simulation (also known as the Monte Carlo Method) which allows you to see all the possible outcomes of your decisions and evaluate the impact of risk, enabling better decision-making under uncertainties.

Monte Carlo Simulation description:

Monte Carlo simulation is a computerized mathematical technique used to generate random sample data for numerical experiments based on some known distribution. This method is applied to quantitative analysis of risk and problems with decision-making. This approach is used by professionals with different profiles such as finance, project management, energy, manufacturing, engineering, research and development, insurance, oil & gas, transport, etc.

The simulation provides the decision-maker with a range of possible outcomes and the probabilities for any choice of action they will occur. It reveals the extreme possibilities and all potential repercussions for middle-of-the-road decisions.

This method was first utilized in 1940 by scientists working on the atom bomb. This method can be used in situations where an estimate and uncertain decisions such as weather forecast predictions are needed.

Monte Carlo Simulation Methodology:

Monte Carlo simulation performs risk analysis by building models of possible outcomes by substituting a range of values (a distribution of probability) for any factor with inherent uncertainty. It then calculates outcomes over and over, using different set of random values from the probability functions every time. A Monte Carlo simulation may require thousands or tens of thousands of recalculations, depending on the number of uncertainties and the ranges defined for them, before it is complete. Simulation from Monte Carlo produces distributions of possible outcome values.

Variables may have different probabilities of different outcomes by using distributions of probabilities. Distributions of chance are a much more practical way to explain the uncertainty in a risk analysis variable.

Monte Carlo Simulation Important Characteristics:

- Random samples must be generated at its output.
- The distribution of its inputs must be known.
- Its outcome must be known during an experiment.

Model explanation:

Advantages:

- Probabilistic Results:

  Results indicate not just what could happen but how probable every outcome is.

- Graphical Results:

  Because of the data produced by a Monte Carlo simulation, the development of graphs of different outcomes and their chance of occurrence is simple. That is important for sharing findings with other stakeholders.

- Sensitivity Analysis:

  Deterministic analysis makes it difficult to see, with only a few cases, which variables most impact the outcome. It is easy to see in Monte Carlo simulation which inputs had the greatest effect on the results of the bottom line.

- Scenario Analysis:

  In deterministic models, to see the effects of truly different scenarios it is very difficult to model different combinations of values for different inputs. Using Monte Carlo simulation, analysts can see exactly what inputs, when certain results occurred, had which values together. That is important for further research to be carried out.

- Correlation of Inputs:

  In the simulation of Monte Carlo, interdependent relationships between input variables can be modelled. Representing how, in truth, when some factors go up, others go up or down accordingly is critical for the accuracy.

- Simple to deploy.
- Provides statistical sampling using the computer for the numerical experiments.
- Provides approximate mathematical solutions to problems.
- Can be used for problems of both stochastic and deterministic nature.

Disadvantages:

- Time consuming:

  Since there is a need to generate a lot of sampling to get the desired output.

- Approximation:

  The results of this method are only true-value approximation, not the exact.

The problem that this model is used to solve:

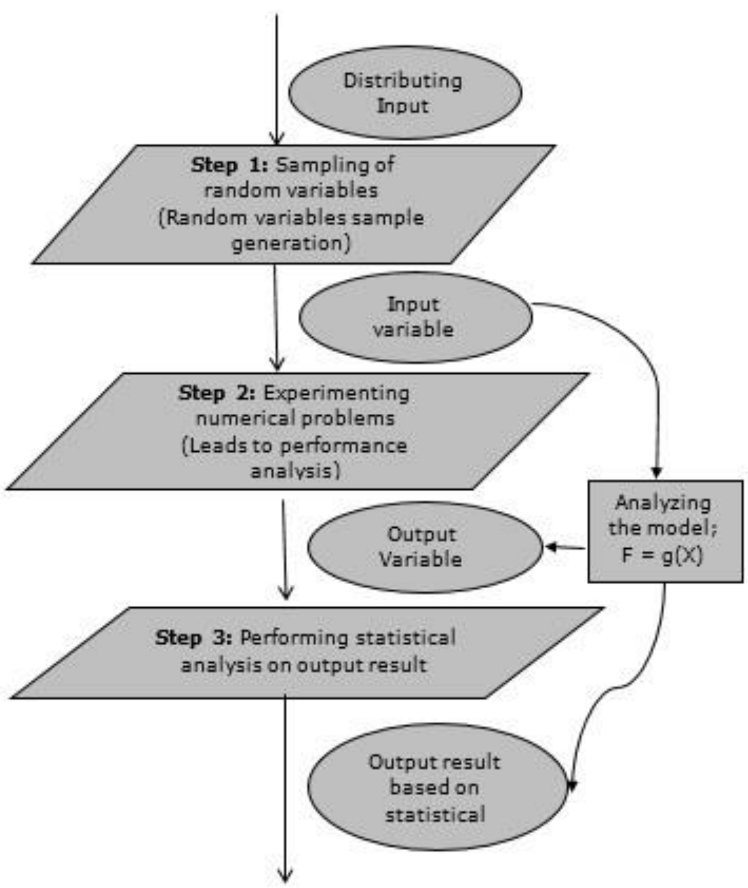
A problem with both of these properties:

- The space for the solution is very broad.
- There are no current stats that would generate any probabilities.

Monte Carlo is used for random sampling of the space in such situations. The more you sample space the more accurate the answer is.

The classic example is when knowing the area of a very irregular form is required. Calculating the exact correct answer may be difficult but Monte Carlo can be used to get a good estimate.

Flow Diagram of Monte Carlo Methodology:



Application:

Table1.js

Code:

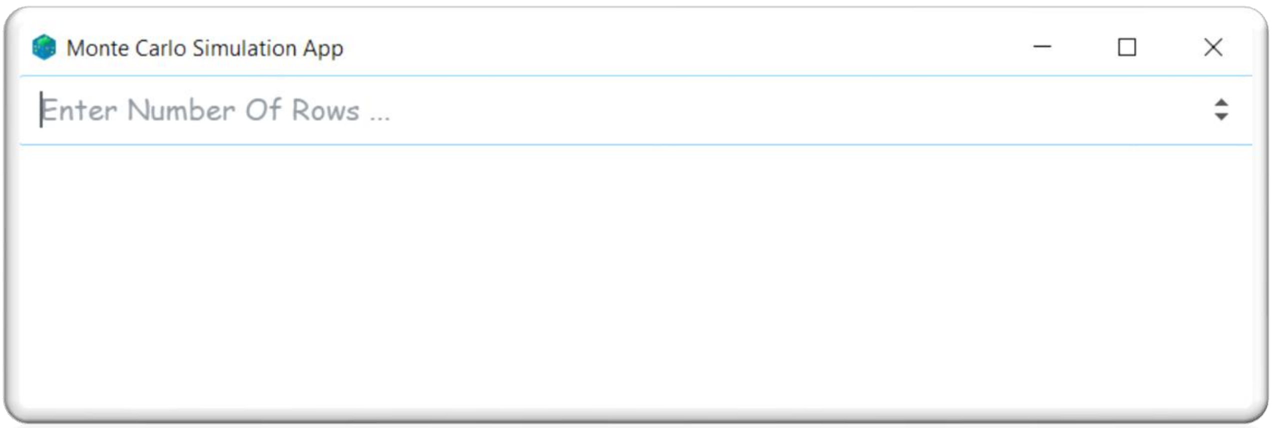
```
import React, { useContext } from "react";
import { Table, Input } from "reactstrap";
import { AppContext } from "../contextAPI/appContext";
const Table1 = () => {
 const {
  rows,
  onInputChangeD,
  demands,
  onInputChangeF,
  Frequency,
  prob,
  cum,
  randomNumbers,
 } = useContext(AppContext);
 return (
  <Table borderless hover>
   <thead>
    <tr>
     <th>Demand</th>
     <th>Frequency</th>
     <th>P{"ROBABILITY".toLowerCase()}</th>
     <th>C{"UMULATIVE".toLowerCase()}</th>
     <th>Number-Range</th>
    </tr>
   </thead>
   <tbody>
    {(() => {
     let eleArray = [];
```

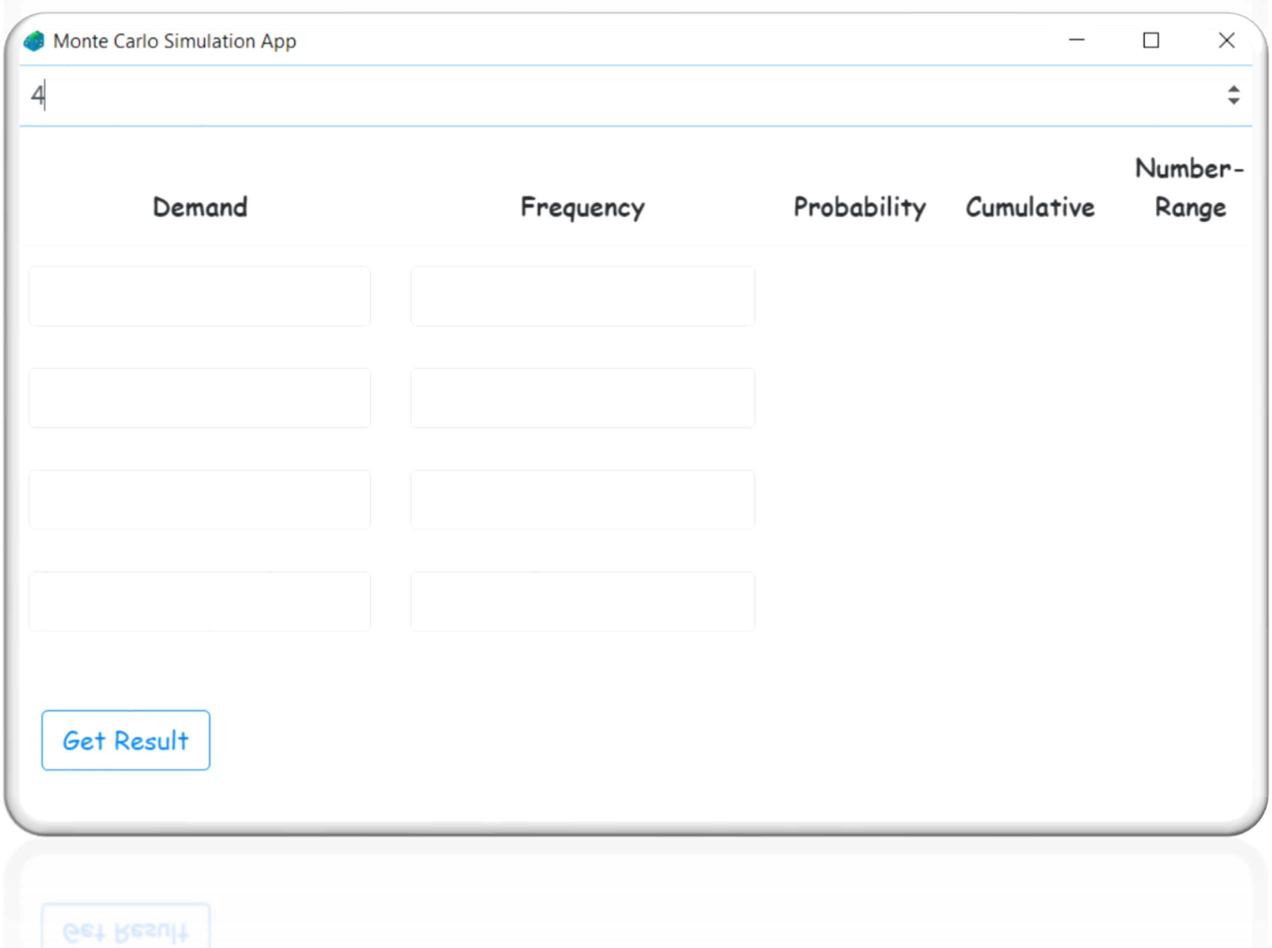
```
for (let i = 1; i <= rows; i++) {
  eleArray.push(
    <tr key={`${i}tr`}>
      <td className="inputter">
        <Input
          type="number"
          name={`d${i}`}
          onChange={onInputChangeD}
          value={demands[`d${i}`]}
        />
      </td>
      <td className="inputter">
        <Input
          type="number"
          name={`f${i}`}
          onChange={onInputChangeF}
          value={Frequency[`f${i}`]}
        />
      </td>
      <td>{prob ? prob[i - 1] : null}</td>
      <td>{cum ? cum[i - 1] : null}</td>
      <td>
        {randomNumbers[i - 1]
          ? `${randomNumbers[i - 1][0]} to ${
              randomNumbers[i - 1][randomNumbers[i - 1].length - 1]
            }`
          : null}
      </td>
    </tr>
  );
}
return eleArray;
```

```
      })()}
    </tbody>
  </Table>
 );
};
export default Table1;
```

Snapshots from the application:

Arbitrary numbers are added to test the application





Monte Carlo Simulation App

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Demand	Frequency	Probability	Cumulative	Number-Range
3	2	0.22	0.22	1 to 22
5	1	0.11	0.33	23 to 33
6	4	0.44	0.77	34 to 77
3	2	0.22	0.99	78 to 99

Get Result

Get Result

Ten days simulation

simulated Average daily demand is 4.5 and expected daily demand is 4.51 and You Can Try Again

Day	Random Number	Simulated demand
1	35	6
2	63	6
3	10	3
4	93	3
5	21	3
6	78	3
7	16	3
8	55	6
9	46	6
10	64	6

A Bonus solved question to illustrate how to apply the Monte Carlo simulation:

Grear Tire Company has produced a new tire with an estimated mean lifetime mileage of 36,500 miles. Management also believes that the standard deviation is 5,000 miles and that tire mileage is normally distributed. To promote the new tire, Grear has offered to refund some money if the tire fails to reach 30,000 miles before the tire needs to be replaced. Specifically, for tires with a lifetime below 30,000 miles, Grear will refund a customer $1 per 100 miles short of 30,000. a) For each tire sold, what is the expected cost of the promotion? b) Please perform the simulation for 1000 times, what is the probability that Grear will refund more than $50 for a tire?

Solution:

From the given data:

μ = 36,500

σ = 5,000

Let X be the number of miles reached.

The probability that the tire fails to reach 30,000 miles is:

$$P(X<30{,}000) = P\left(\frac{X-\mu}{\sigma} < \frac{30{,}000-\mu}{\sigma}\right)$$

$$= P\left(Z < \frac{30{,}000-36500}{5000}\right)$$

$$= P\left(Z < \frac{-6500}{5000}\right)$$

$$= P(Z < -1.3)$$

$$= 0.0968 \text{ (Normal dist table)}$$

The probability that it will not reach 30,000 miles is = 0.0968

Now E(X) = 30,000 * 0.0968 = 2904

As $1 per 100 m, the expected cost of the promotion per time = 2904/100 = 29.04

Grear will refund more than $50 for a time as per $1 100 miles.

Then, 50 * 100 = 5000

$$P(X<25{,}000) = P\left(\frac{X-\mu}{\sigma} < \frac{25{,}000-\mu}{\sigma}\right)$$

$$= P\left(Z < \frac{25{,}000-36500}{5000}\right)$$

$$= P\left(Z < \frac{-11{,}500}{5000}\right)$$

$$= P(Z < -2.3)$$

$$= 0.0107$$

= 0.11 As $1 per 100 miles, it should limit as 25,000 for cost of promotion to $2.00

References:

- https://www.epa.gov/
- https://www.palisade.com/
- https://www.tutorialspoint.com/
- https://magicplot.com/wiki/special_symbols
- Essentials of Business Analytics (1st Edition)
- Quantitative analysis for management