

# 60615A : Decision Analysis Monte Carlo Simulation Part I

Prof. Carolina Osorio

Slides of Prof. Erick Delage, in collaboration with Prof.  
Geneviève Gauthier  
Department of Decision Sciences  
HEC Montréal

# Outline

- 1 Introduction
- 2 Generation of pseudo-random numbers

# Outline

- 1 Introduction
- 2 Generation of pseudo-random numbers

# Objective of a Monte Carlo simulation

- In a problem with uncertainty, the value of our objective must be considered as a random variable.
  - Example : generated profit, project's success, magnitude of environmental impact, etc.
- Monte Carlo simulation allows one to study the stochastic nature of this random variable.
  - Estimation of the expected value : expected profit, expected impact, ...
  - Probability distribution : probability of success, distribution function, variance, percentiles, ...
- A Monte Carlo simulation enables the comparison of different alternatives.
- It does not directly enable the optimization of a decision.

# Monte Carlo simulation procedure

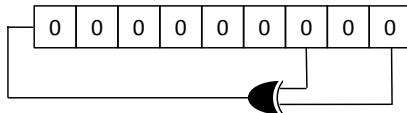
- ➊ Design the influence diagram.
- ➋ Describe the influence relations associated to each box.
- ➌ Choose the alternatives to evaluate.
  - Choose the function that maps influence variables to actions.
- ➍ Randomly draw  $M$  scenarios of realizations of the random variables.
  - Start with the random variables that are not influenced and generate a realization according to their distribution.
  - For each variable that are only influenced by already computed variables, generate a realization according to the conditional distribution.
  - Repeat until a realization has been generated for all variables.
  - Evaluate the objective for this scenario of realization.
- ➎ Analyze some statistics that are based on the empirical distribution obtained for the objective.
- ➏ Estimate the level of confidence of each estimate to find out if more scenarios should be used.

# Outline

- 1 Introduction
- 2 Generation of pseudo-random numbers

# Generation of Bernoulli events ( $p = 0.5$ )

- Some devices really simulate this event through a physical phenomena (e.g. thermal noise).
- Our computers simulate it using a deterministic process.
- This is the difference between random and pseudo-random.
- Linear Feedback Shift Register (see Excel file) :
  - This system generates a sequence of 0's and 1's, such that we cannot distinguish the sequence from a random sequence (with 50% chance that the next value is 1).



# Uniform distribution on the interval $[0, 1]$

«How to generate a uniform value between 0 and 1 using a quarter (25 cent coin) ?»

Iterative Process (see Excel file) :

- Divide the interval in two sub-intervals of the same size.
- Execute a fair coin toss : if tail, keep the left interval, else the right.
- After  $k$  tosses, the size of the interval is  $1/2^k$ .
- Stop when the resulting interval is small enough.
- Keep as a random value the average value on this interval.



# Generating a discrete variable I

- We want to simulate a random variable taking the values  $\{z_1, z_2, \dots, z_N\}$  with respective probabilities  $\{p_1, p_2, \dots, p_N\}$ .
- Method : generate  $U$  uniformly on  $[0, 1]$  and draw  $Z$  according to the table :

If $U \in [a, b]$	then $Z =$
$[0, p_1]$	$z_1$
$] p_1, p_1 + p_2 ]$	$z_2$
$] p_1 + p_2, p_1 + p_2 + p_3 ]$	$z_3$
$\dots$	$\dots$
$] p_1 + \dots + p_{n-1}, 1 ]$	$z_n$

# Generation of a discrete variable II (Additional Information)

- We want to simulate a random variable taking the values  $\{z_1, z_2, \dots, z_N\}$  with respective probabilities  $\{p_1, p_2, \dots, p_N\}$ .
- Theorem : if  $U$  is uniform on  $[0, 1]$ , then

$$V = \sum_{i=1}^N z_i \mathbb{1} \left\{ \sum_{j=1}^{i-1} p_j \leq U < \sum_{j=1}^i p_j \right\}$$

follows the described discrete distribution.

- Proof (AI) :

$$\begin{aligned} P(V = z_i) &= P \left( \sum_{j=1}^{i-1} p_j \leq U \leq \sum_{j=1}^i p_j \right) = F_U \left( \sum_{j=1}^i p_j \right) - F_U \left( \sum_{j=1}^{i-1} p_j \right) \\ &= \sum_{j=1}^i p_j - \sum_{j=1}^{i-1} p_j = p_i. \end{aligned}$$

# Generating a continuous random variable

Inverse transform method (see Excel file) :

- Assumption : the cumulative distribution function  $F : \mathbb{R} \rightarrow [0, 1]$  is continuous and strictly increasing
- Method : if  $U$  is a uniformly distributed random variable over  $[0, 1]$ , then  $V = F^{-1}(U)$  is distributed according to  $F$
- Proof (AI) :

$$F_V(v) = P(F^{-1}(U) \leq v) = P(U \leq F(v)) = F(v)$$

- Example : exponential distribution,
  - $F(z) = (1 - \exp(-\lambda z))\mathbb{I}\{z \geq 0\}$
  - $V = F^{-1}(U) = -(1/\lambda) \ln(1 - U)$
- Example in Excel : «=norminv(rand();0;1)» generates a random value distributed according to the normal distribution (see Excel file)

# Generating a random vector

- We want to generate a scenario of realizations for a vector of random variables for which the joint probability function is  $P_Z(z_1, z_2, z_3, \dots, z_n)$ .
- Compute the marginal and conditional probability functions.

$$P_1(Z_1 = y) = \sum_{z_2} \sum_{z_3} \cdots \sum_{z_n} P_Z(y, z_2, z_3, \dots, z_n)$$

$$P_2(Z_2 = y|z_1) = \sum_{z_3} \sum_{z_4} \cdots \sum_{z_n} P(z_1, y, z_3, \dots, z_n) / P_Z(Z_1 = z_1)$$

...

$$P_n(Z_n = y|z_1, \dots, z_{n-1}) = P_Z(z_1, \dots, z_{n-1}, y) / P_Z(Z_1 = z_1, \dots, Z_{n-1} = z_{n-1})$$

- Method : if  $(V_1, V_2, \dots, V_n)$  is a set of random variables generated as above, then  $V$  is distributed following  $P_Z$ .

$$V_1 \sim P_1(Z_1) \quad V_2 \sim P_2(Z_2|V_1) \quad \dots \quad V_n \sim P_n(Z_n|V_1, V_2, \dots, V_{n-1})$$

# Rejection method - Theory (AI)

- Hypothesis :  $f_Z$  &  $f_V$  are density functions on  $\mathbb{R}^n$

- ① We know how to simulate  $V$ .

- ② There exist a constant  $c$  such as  $f_Z(z) \leq cf_V(z)$ ,  $\forall z \in \mathbb{R}^n$

- Method : consider a sequence of pairs  $(U_1, V_1), (U_2, V_2), \dots$ , where each  $U_i$  is independent and uniformly distributed on  $[0, 1]$  and each  $V_i$  is independent and generated following  $f_V$ . If  $i^*$  is the 1<sup>st</sup> index  $i$  such that  $cU_i \leq f_Z(V_i)/f_V(V_i)$ , then  $V_{i^*}$  is distributed according to  $f_Z$ .

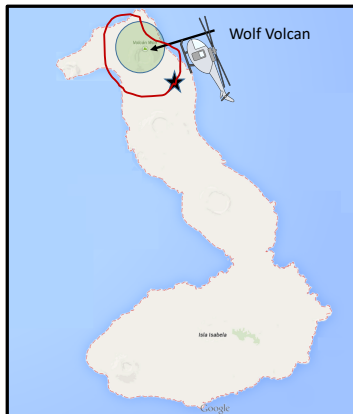
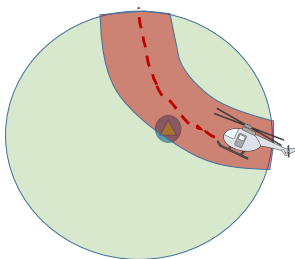
- Proof when  $n = 1$  (AI) :

$$\begin{aligned}
 P(V_{i^*} \leq z) &= P\left(V \leq z \mid cU \leq \frac{f_Z(V)}{f_V(V)}\right) = \frac{P(V \leq z \text{ \& } cU \leq f_Z(V)/f_V(V))}{P(cU \leq f_Z(V)/f_V(V))} \\
 &\propto \int_{-\infty}^z P\left(cU \leq \frac{f_Z(y)}{f_V(y)}\right) f_V(y) dy = \int_{-\infty}^z (1/c) \frac{f_Z(y)}{f_V(y)} f_V(y) dy \\
 &= (1/c) F_Z(z) \Rightarrow P(V_{i^*} \leq z) = P(Z \leq z)
 \end{aligned}$$

- If  $c \gg 1$ , we can wait a long time for  $V_{i^*}$  ( $E[i^*] = c$ )

# Example of random generation I

What are your chances of seeing a Galapagos iguana during a helicopter tour of the Wolf volcano?



# Example of random generation II

Generate a point uniformly in a disc of radius 1

$$f_Z(z_1, z_2) = (1/\pi) \mathbb{I}\{z_1^2 + z_2^2 \leq 1\}$$

- Consider  $V$  uniform on the square  $[-1, 1] \times [-1, 1]$

$$f_V(v_1, v_2) = (1/4) \mathbb{I}\{-1 \leq v_1 \leq 1 \text{ \& } -1 \leq v_2 \leq 1\}$$

- We can generate  $V$  by simulating  $V_1 \sim U(-1, 1)$  and  $V_2 \sim U(-1, 1)$  and assemble  $V = (V_1, V_2)$
- Let's use the rejection method (see Excel file) :

- We choose  $c$  :

$$c = \inf\{c | f_Z \leq cf_V\} = \inf\{c | (1/\pi) \leq c/4\} = 4/\pi$$

- We accept  $(U, V_1, V_2)$  if

$$U \leq \frac{\pi}{4} \frac{(1/\pi) \mathbb{I}\{V_1^2 + V_2^2 \leq 1\}}{(1/4) \mathbb{I}\{-1 \leq V_1 \leq 1, -1 \leq V_2 \leq 1\}} = \mathbb{I}\{V_1^2 + V_2^2 \leq 1\}$$

I.e, if  $V_1^2 + V_2^2 \leq 1$ , we say  $Z_1 = V_1$  and  $Z_2 = V_2$