MG26018 Simulation Modeling and Analysis
仿真建模与分析

Lecture 1: Introduction to Simulation

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Contents

What is Simulation?

- *Simulation* (仿真) is the imitation of the operation of a real-world process or system over time.
    - Done by hand or (usually) on a computer;
    - Involves the generation and observation of an artificial history of a system;
    - Draw inferences about the characteristics of the real system.

- Simulation is EVERYWHERE!

Figure: Pilot Training in Boeing 787 Flat Panel Trainer (*from* Boeing)

Figure: Airport Simulation (*by Vancouver Airport Services*)

[Video: https://www.youtube.com/watch?v=JuXwEbAvk2Q]

Figure: Typhoon Simulation (*image* by *Atmoz* / *CC BY 3.0*)

Figure: Financial Analysis

- It is often too costly or even impossible to do physical studies in reality with the actual system.
  - May be *disruptive*, *expensive*, *dangerous*, or *rare*.

- The mathematical model (will be defined shortly) which can well represent the real problem, may be very *difficult* to solve.
  - You can only solve it with high *simplification*.

- With simulation technique, we can easily make change and observe the effect, while keeping high fidelity.

Why Simulation?

- Simulation can be used as both an *analysis tool* and a *design tool*.

1. An analysis tool: To answer "what if" questions about the existing real-world system.
   - E.g., try alternative layout of a production line, try other staff shifts of a service center, test a financial system in some extreme situation, etc.

2. A design tool: To study systems in the design stage, before they are built.
   - E.g., evaluate designs and operations for new transportation facilities, service organizations, manufacturing systems, etc.

- Simulation is also an important type of numerical methods.

- This is the focus of the course!
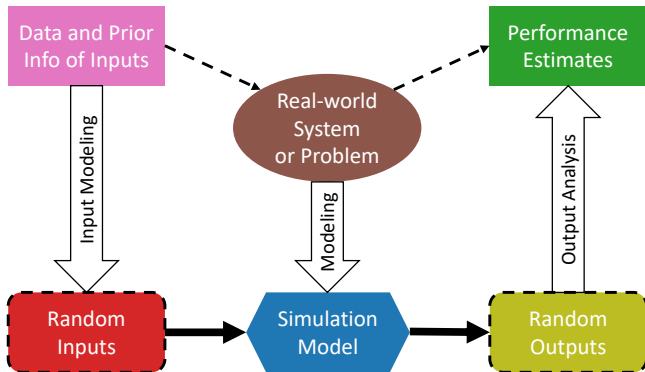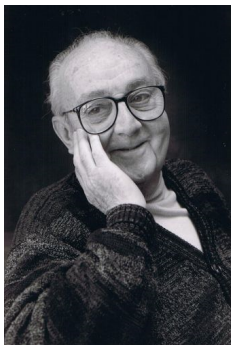

Figure: Basic Paradigm of A Simulation Study

- A model is a representation of a system or problem.
  - A set of assumptions and/or approximations about how the system works will often be imposed.
  - It is only necessary to consider those aspects that affect the problem under investigation.
  - However, the model should be sufficiently detailed to draw *valid* conclusions about the real system or problem.
  - The trade-off: simplicity vs. accuracy.

- Physical model vs. Mathematical model
  1. Physical model: a scaled-down (or -up) version of the system.
  2. Mathematical model: uses symbolic notation and mathematical equations to represent the system.

- Instead of doing physical studies with the actual system in real world, we can study the model.
  - It will be much easier, faster, cheaper, and safer!

- A simulation model is a particular type of mathematical model.

❝All models are wrong,
but some are useful.**❞**

— *George E. P. Box*

George E. P. Box (1919.10 – 2013.03) was a British statistician, who worked in the areas of quality control, time-series analysis, design of experiments, and Bayesian inference. He has been called "one of the great statistical minds of the 20th century".

- When a mathematical model is simple enough, we can solve it
  - *analytically*, with mathematical tools like algebra, calculus, probability theory.
  - *numerically*, with computational procedures (e.g., solving a quintic equation).

- But not all mathematical models can be "solved".

- In simulation, the mathematical models (more specifically, simulation models) are run rather than solved:
  - Artificial history of the system is *generated* from the model assumptions;
  - Observations of system status are *collected* for analysis;
  - System performance measures are *estimated*.

- Essentially, running simulation is still one type of numerical methods.
  - Real-world simulation models can be large, and such runs are usually conducted with the aid of a computer.

- Simulation models may be classified as being *static* or *dynamic*.

❶ Static: Time does not play a **natural** role.
  - Example 1 – Finance: evaluate portfolio return and risk.
  - Example 2 – Project Management: evaluate projects payoff in different scenarios.
  - Sometimes called Monte Carlo (蒙特卡洛) simulation.
  - Often used in the complex numerical calculation in financial engineering (金融工程), computational physics, etc.

❷ Dynamic: Time does play a **natural** role.
  - Example 1 – Logistics Management: evaluate the efficiency of a terminal.
  - Example 2 – Service Management: evaluate waiting time of customers under different staff shifts.
  - Often used to simulate the logistics/transportation/service systems, whose status naturally changes over time.

- Simulation models may be classified as being *deterministic* or *stochastic*.

❶ Deterministic: Everything is known with **certainty**.
  - E.g., patients arrive at a hospital precisely on schedule, the service time is precisely fixed, the transfer among different units is pre-determined.

❷ Stochastic: **Uncertainty** exists.
  - E.g., arrival times and service times of patients have random variations, the transfer is random.
  - Used much more often (uncertainty is more or less involved in a real-world system).

- Simulation models may be classified as being *discrete* or *continuous*.

❶ Discrete: System states change only at **discrete** time points.
  - E.g., the number of customers in the bank, changes only when a customer arrives or leaves after service (*left fig*).

❷ Continuous: System states change **continuously** over time.
  - E.g., the head of water (水位) behind a dam changes continuously during a period of time (*right fig*).
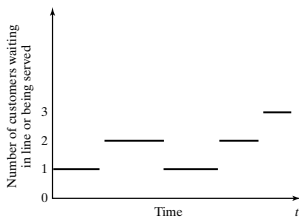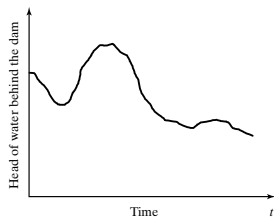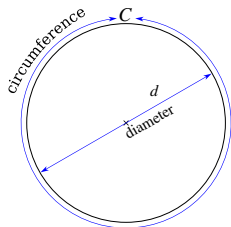

Figure: Discrete State (*from Banks et al. (2010)*)

Figure: Continuous State (*from Banks et al. (2010)*)

- In summary, simulation models may be classified as being *static* or *dynamic*, *deterministic* or *stochastic*, and *discrete* or *continuous*.

- For most operational decision-making problems, the suitable simulation models are *dynamic*, *stochastic* and *discrete*.
  - The simulation is called Discrete-Event System Simulation (离散事件系统仿真).
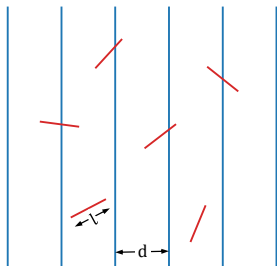 - It is the main **focus** of this course.

- The mathematical constant π, is originally defined as the ratio of circle's circumference to its diameter.

$$\pi = \frac{\text{circumference}}{\text{diameter}} = 3.14159\ldots$$

- It was considered as a quite difficult problem in the history of mankind to find the value of π.

- Buffon's Needle (布丰投针)
  - Buffon, a French mathematician, in 1733 (1777) did a static simulation (by hand), which can be used to estimate π.
  - Drop a needle of length l onto the floor with parallel lines d apart, where $l < d$.
  - Suppose the needle is *equally likely* to fall anywhere.

- $\mathbb{P}(\text{needle crosses a line}) = \dfrac{2l}{\pi d}$.

- If Buffon repeats the experiment for n times (i.e., drops n needles), and let h denote the number of needles crossing a line, then,

$$\mathbb{P}(\text{needle crosses a line}) = \frac{2l}{\pi d} \approx \frac{h}{n}.$$

- So, $\pi \approx \frac{2ln}{dh}$.

- Let $d = 2l$, then $\pi \approx n/h$.

- The approximation gets more and more accurate when n increases.
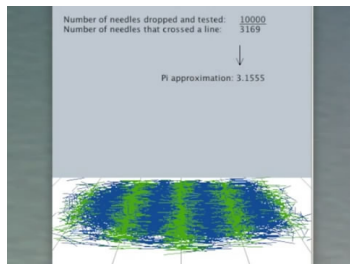
- Try it out!
  https://mste.illinois.edu/activity/buffon
  http://datagenetics.com/blog/may42015/index.html

Figure: A Computer Simulation (*by Jeffrey Ventrella*)
[Video: https://www.youtube.com/watch?v=kazgQXaeOHk]

- Now consider another simulation to estimate π.
  - Randomly throw n dots to a square.
  - Suppose the dots are *equally likely* to fall anywhere inside the square.
  - Let h denote the number of dots in the circular sector.
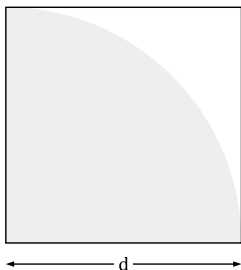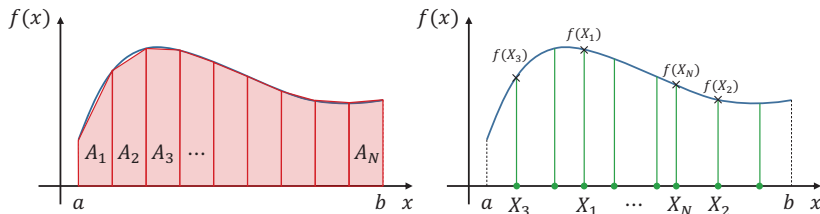

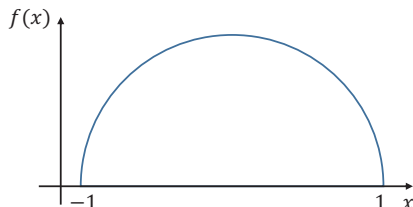Figure: Animation (*image* by *nicoguaro* / *CC BY 3.0*)

- $\mathbb{P}(\text{dot in sector}) = \dfrac{\text{sector area}}{\text{square area}} = \dfrac{\pi d^2/4}{d^2} \approx \dfrac{h}{n}. \quad \Rightarrow \quad \pi \approx \dfrac{4h}{n}.$

- Visit `https://xiaoweiz.shinyapps.io/calPi` for interaction.

- Consider a numerical integration (数值积分) $\int_a^b f(x)\mathrm{d}x$.

- Trapezoidal rule (梯形法) (*left fig*)
  1. Divide the area into N parts.
  2. $\int_a^b f(x)\mathrm{d}x \approx A_1 + A_2 + \cdots + A_N$.

- Monte Carlo method (*right fig*)
  1. Randomly sample N points on $[a, b]$ from Uniform$[a, b]$.
  2. $\int_a^b f(x)\mathrm{d}x \approx \frac{b-a}{N}\left[f(X_1) + f(X_2) + \cdots + f(X_N)\right]$.

- Monte Carlo method will be much more "**efficient**" when the dimension of x is high! (E.g., $\int_{[a,b]^d} f(\boldsymbol{x})\mathrm{d}\boldsymbol{x}$ for large d.)

- Recall the numerical integration problem $\int_a^b f(x)\mathrm{d}x$.

- Let $f(x) = \sqrt{1-x^2}$, $a = -1$, $b = 1$.

- Then, $\int_{-1}^1 \sqrt{1-x^2}\mathrm{d}x = \pi/2$.

- So we have another way to estimate π using Monte Carlo simulation (provided we know how to compute square root).

- There is a system:
  - Two components work as active and spare, so the system fails if both are failed.
  - Time to next failure is equally likely 1, 2, 3, 4, 5 or 6 days (assume no memory).
  - Repair takes exactly 2.5 days (only one at a time).

- What can we say about the time to failure for this system?

- Let's run a simulation by hand!
  - The **state** of the system is the number of functional components.
  - The **events** are the failure of a component and the completion of repair.

| | | Event Calendar | |
Clock	System State	Next Failure	Next Repair
0	2	$0 + 5 = 5$	∞
5	1	$5 + 3 = 8$	$5 + 2.5 = 7.5$
7.5	2	8	∞
8	1	$8 + 6 = 14$	$8 + 2.5 = 10.5$
10.5	2	14	∞
14	1	$14 + 1 = 15$	$14 + 2.5 = 16.5$
15	**0**	∞	16.5

- We can observe:
  - Time to failure $= 15$
  - Average number of functional components $=$
    $$\frac{1}{15-0}\left[2(5-0) + 1(7.5-5) + 2(8-7.5) + 1(10.5-8) + 2(14-10.50 + 1(15-14)\right]$$
    $$= \frac{24}{15}$$
- Some questions:
  - How to deal with the randomness?
  - How to generate the time interval of component failure?

Course Outline

- Introduction to Simulation
- Queueing Models
- Random Variate Generation
- Input Modeling
- Verification and Validation of Simulation Models
- Output Analysis I: Single Model
- Simulation in Excel and Arena
- Output Analysis II: Comparison and Optimization