



# Introduction to Simulation

**Comparing Systems** 



## **Comparing Designs**

We often want to compare different system designs

This is one of the most important applications of simulation

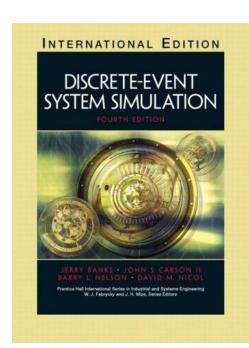
### **Examples**:

- Different scheduling policies (queueing strategies)
- Different system structures
- Different times or probabilities
- Validation

## **Background Reading**

#### Relevant sections of the book:

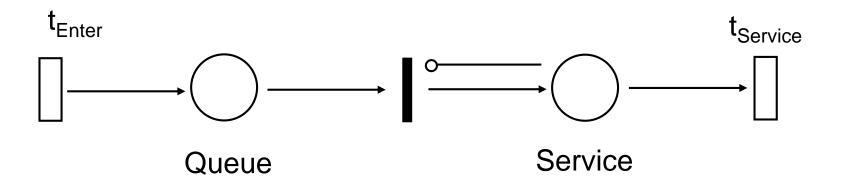
**12.1** 



## **Example: Simple Queue**

Arrivals are  $\sim \exp(11)$ 

Solution  $S_1$ : One server with service time  $\sim \exp(10)$ 

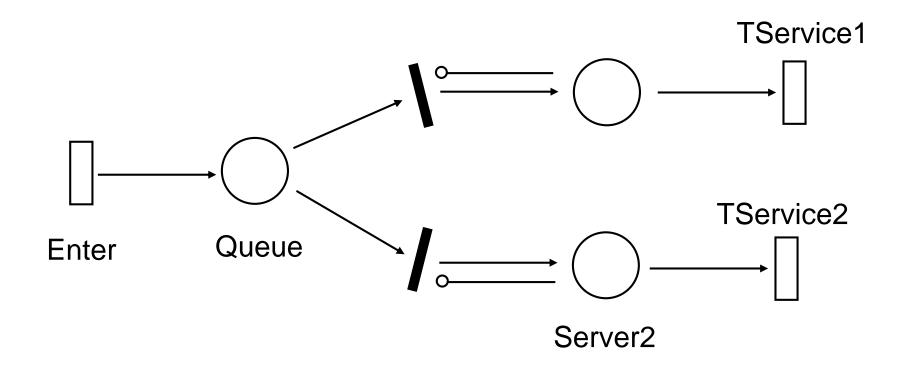




## **Example: Simple Queue**

Solution  $S_2$ : Two servers with service time  $\sim \exp(20)$ 

Which system is better?





## **Example: Simple Queue**

Observe the average queue length at T=10000

Simulate both systems and compare results:

Replication	1	2	3	4	5	6	7	8	9	10
Shorter Q.	S <sub>2</sub>	$S_1$	$S_2$	$S_2$	$S_2$	$S_2$	S <sub>1</sub>	$S_2$	$S_1$	$S_2$

Which system is better?

#### The General Procedure

Perform  $R_1$  replications on  $S_1$ , obtaining  $Y_{r1}$   $r=1...R_1$ 

Perform  $R_2$  replications on  $S_2$ , obtaining  $Y_{r2}$   $r=1...R_2$ 

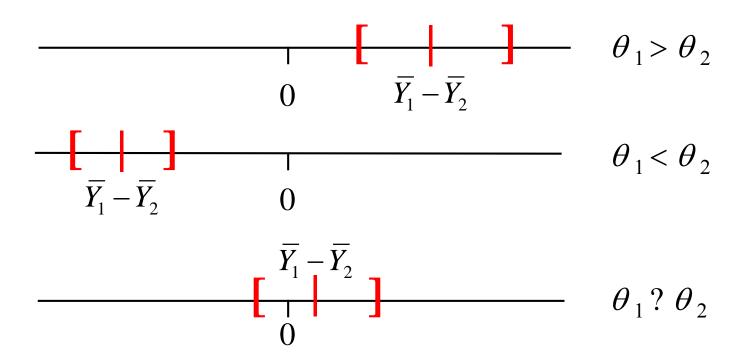
Compute averages  $\overline{Y}_1$ ,  $\overline{Y}_2$ 

Compute a confidence interval around  $\overline{Y}_1 - \overline{Y}_2$ :

$$(\overline{Y_1} - \overline{Y_2}) - \hat{\sigma} \cdot t_{\alpha/2, f} \le \theta_1 - \theta_2 \le (\overline{Y_1} - \overline{Y_2}) + \hat{\sigma} \cdot t_{\alpha/2, f}$$

### The General Procedure

There are three possibilities for the confidence interval:



## Significance

We consider the difference in system performance ...

### Practical significance:

"The actual difference in performance is significant with respect to our goals."

### Statistical significance:

"Is our simulation experiment good enough to reveal the difference between the systems, or are we just seeing the result of randomness?"

## Computing $\sigma$

We need the value of  $\sigma$  for the confidence interval

$$(\overline{Y_1} - \overline{Y_2}) - (\hat{\overline{\sigma}}) t_{\alpha/2,f} \leq \theta_1 - \theta_2 \leq (\overline{Y_1} - \overline{Y_2}) + (\hat{\overline{\sigma}}) t_{\alpha/2,f}$$

There are three cases to be considered:

- Independent sampling with equal variances
- Independent sampling with unequal variances
- Correlated sampling

## Indep. Sampling, Equal Var.

### We make the following assumptions:

- We will perform independent replications
- The variances in  $Y_1,\ Y_2$  are (approximately) equal

We can pool our estimates as follows:

$$S^{2} = \frac{(R_{1} - 1)S_{1}^{2} + (R_{2} - 1)S_{2}^{2}}{R_{1} + R_{2} - 2}$$

We then obtain  $\sigma$  using:  $\sigma = S \sqrt{\frac{1}{R_1} + \frac{1}{R_2}}$ 

The confidence interval then has  $R_1 + R_2 - 2$  d.o.f.

## Indep. Sampling, Unequal Var.

What if the variances in  $\overline{Y}_1$ ,  $\overline{Y}_2$  are not equal?

Then we must use the following for the standard error:

$$\sigma = \sqrt{\frac{S_1^2}{R_1} + \frac{S_2^2}{R_2}}$$

The formula for the number of d.o.f. is very complicated! (Refer to literature)



Until now, replications were always independent

One technique, however, does this differently

## This is the method of *Correlated Sampling*

- It is the most common example of variance reduction
- It is used to improve the confidence intervals
- It can be difficult to implement
- It can also be very effective

#### Motivation:

- The width of our confidence interval depends on  $\sigma$
- Is there a way to reduce the size of  $\sigma$ ?

$$\sigma^2$$
 is an estimator for  $var(\overline{Y_1} - \overline{Y_2})$ 

In the general case, we have

$$\operatorname{var}(\overline{Y_1} - \overline{Y_2}) = \operatorname{var}(\overline{Y_1}) + \operatorname{var}(\overline{Y_2}) - 2\operatorname{cov}(\overline{Y_1}, \overline{Y_2})$$

Or, more specifically, (with  $R_1 = R_2 = R$ ):

$$\operatorname{var}(\overline{Y_1} - \overline{Y_2}) = \frac{\sigma_1^2}{R} + \frac{\sigma_2^2}{R} - \frac{2\rho_{12}\sigma_1\sigma_2}{R}$$

We have 
$$\operatorname{var}(\overline{Y_1} - \overline{Y_2}) = \frac{\sigma_1^2}{R} + \frac{\sigma_2^2}{R} - \frac{2\rho_{12}\sigma_1\sigma_2}{R}$$

 $(\rho_{12})$  is the correlation)

Therefore, if we could achieve  $\rho_{12} > 0$  ...

- We could reduce  $var(\overline{Y_1} \overline{Y_2})$  ...
- And thus reduce the width of the C.I.

How can we achieve a positive correlation between  $\overline{Y}_1$ ,  $\overline{Y}_2$ ?

#### Idea:

Use the same random numbers in both models

### More precisely:

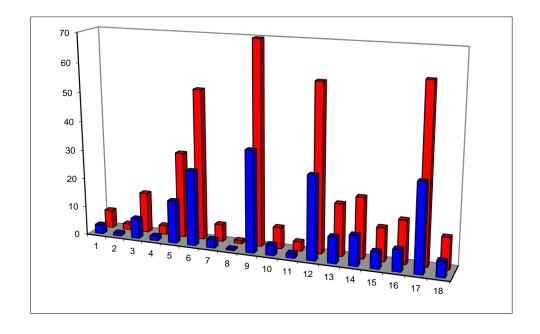
- Each replication uses different random numbers
- In each replication, use the same RNs for each model

#### Then,

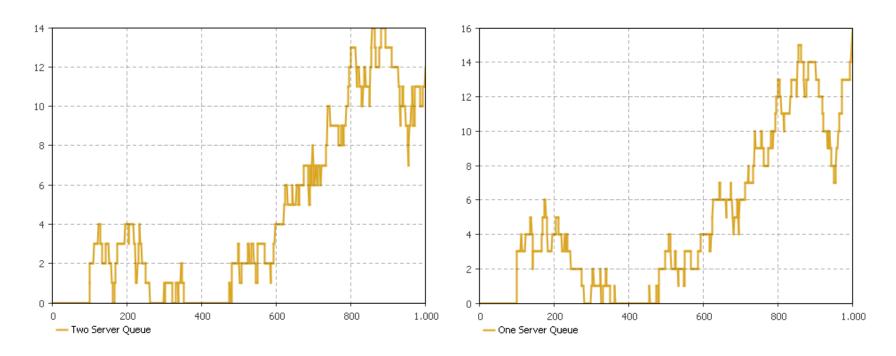
- Different replications will be independent
- Every pair of results  $Y_{r1}$ ,  $Y_{r2}$  will be positively correlated

### Example: Single-server and two server comparison

- Use same RNs for arrival times and service times
- We get *identical* arrival times for both models
- We get *similar* service times for both models:



### The result is very similar behaviour for queue lengths:

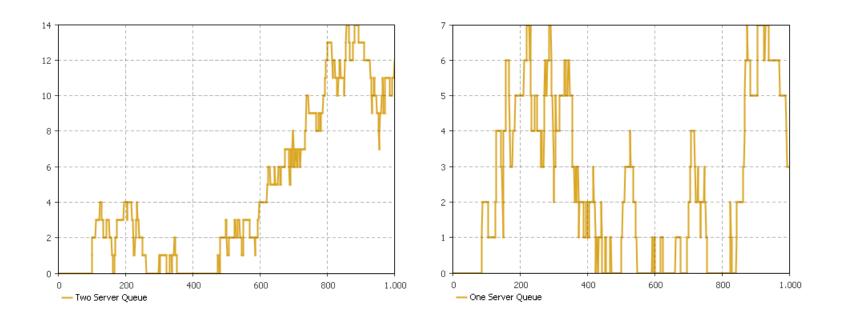


The variance of the difference between these is small

## **Independent Sampling**

### Compare with the standard case using independent RN:

The result is different behaviour for queue lengths:



The variance of the difference between these is large

### Algorithm for comparing two systems:

• Compute 
$$D_r = Y_{r1} - Y_{r2}$$

• Compute 
$$\overline{D} = \frac{1}{R} \sum D_r$$

• Compute 
$$S^2 = \frac{1}{R-1} \sum (D_r - \overline{D})^2$$

• Compute 
$$\sigma = \frac{S}{\sqrt{R}}$$

• Choose  $\alpha$  and compute the confidence interval

#### If the correlation is positive...

- The variance will be smaller than in the independent case
- Our C.I. should be narrower

#### Plus ...

We get this improvement at no extra cost!

#### **But:**

How to implement common random numbers?

#### The main idea:

 Each random number used in model 1 must be used for the same purpose in model 2

i.e. the random numbers must be *synchronised* 

### Example:

 The same random number must used to generate the *i*th arrival time in model 1 and in model 2



If the models are very different, this might be difficult

#### Important principles:

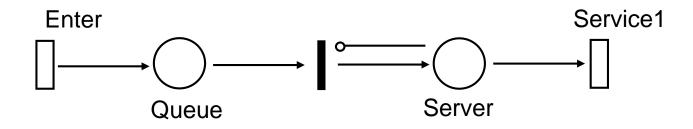
- The systems should be subjected to similar load
- The systems should show similar reactions
- Simulate incomparable subsystems independently

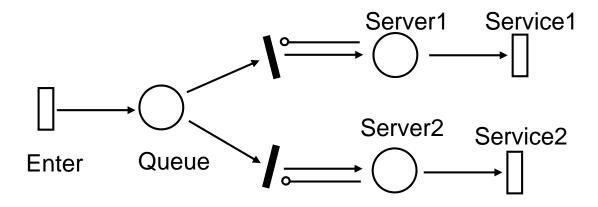
#### Solution:

- Use multiple random number streams
- Assign one stream to the same activity in each model

N.B. This does *not* guarantee a reduction in the variance!

## Example: Compare one- and two-server models





Results ( $\alpha = 0.1, R = 100$ ):

	Indep.	Arr.	Serv.	Both
$\rho_{12}$	0.001	0.539	0.37	0.996
$S^2$	15.317	7.584	9.775	0.057
width of c.i.	1.552	1.092	1.24	0.094



## **Learning Goals**

### Learning questions for the exam:

- What is meant by practical and statistical significance?
- What are synchronised random numbers?
- How does the method of correlated sampling work?
- What is the key idea behind the method of correlated sampling?
- How does the method of correlated sampling achieve a reduced confidence interval at no extra cost?
- What conditions must be achieved in order that the method of correlated sampling can work?