# Systems Simulation Chapter 7: Random-Number Generation Systems Simulation Chapter 7: Random-Number Generation Fatih Cavdur fatihcavdur@uludag.edu.tr April 22, 2014

Systems Simulation Chapter 7: Random-Number Generation

### Introduction

- Random Numbers (RNs) are a necessary basic ingredient in the simulation of almost all discrete systems.
- Most computer languages have a subroutine, object or function that generates a RN.
- Similarly, simulation languages generate RNs that are used to generate event times and other random variables.
- We will look at the generation of RNs and some randomness tests in this chapter. Next chapter will show how we can use them to generate RVs.

### Properties of RNs

- A sequence of RNs,  $R_1, R_2, \ldots$ , must have two important statistical properties: uniformity and independence.
- Each RN, *R<sub>i</sub>* must be an independent sample drawn from a continuous uniform distribution between 0 and 1.

$$f(r) = \begin{cases} 1, & 0 \le r \le 1\\ 0, & \text{otherwise} \end{cases}$$
$$E(R) = \int_0^1 r dr = \frac{1}{2}$$

$$V(R) = E(R^2) - [E(R)]^2 = \frac{1}{12}$$

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### Properties of RNs

Some Consequences of Uniformity and Independence

- If the interval [0, 1] is divided into *n* classes (sub-intervals) of equal length, the expected number of observations in each interval is N/n, where *N* is the total number of observations.
- The probability of observing a value in a particular interval is independent of the previous values drawn.

Systems Simulation Chapter 7: Random-Number Generation └─ Generation of Pseudo-RNs

### Generation of Pseudo-RNs

Problems and Errors

- Numbers might not be uniformly distributed.
- Numbers might be discrete-valued.
- The mean / variance of the generated numbers might be too high or too low.
- There might be dependence, such as,
  - autocorrelation
  - numbers successively higher or lower than adjacent numbers
  - several numbers above the mean followed several numbers below the mean

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### Generation of Pseudo-RNs

Important Considerations

- The routine should be fast.
- The routine should be portable.
- The routine should have a sufficiently long cycle.
- The RNs should be replicable (repeatable).
- Most importantly, the generated RNs should closely approximate the ideal statistical properties of uniformity and independence.

Systems Simulation Chapter 7: Random-Number Generation — Techniques for RN Generation — Linear Congruential Method

### Linear Congruential Method

• The linear congruential method (LCM) produces a sequence of integers,  $X_1, X_2, \ldots$  between 0 and m-1 by following a recursive relationship.

$$X_{i+1} = (aX_i + c) \mod m, \quad i = 0, 1, 2, \dots$$
  
 $R_i = \frac{X_i}{m}, \quad i = 1, 2, \dots$ 

- The initial value X<sub>0</sub> is called the seed, *a* is called the multiplier, *c* is the increment and *m* is the modulus.
- If c = 0, it is known as the multiplicative congruential method, and if c ≠ 0, it is called as the mixed congruential method.

#### 

### Linear Congruential Method

Example

• Use the LGM to generate a sequence of RNs with  $X_0 = 27, a = 17, c = 43$  and m = 100.

$$X_0 = 27$$
  

$$X_1 = (17 \times 27 + 43) \mod 100 = 2 \Rightarrow R_1 = \frac{2}{100} = 0.02$$
  

$$X_2 = (17 \times 2 + 43) \mod 100 = 77 \Rightarrow R_2 = \frac{77}{100} = 0.77$$
  

$$X_3 = (17 \times 77 + 43) \mod 100 = 52 \Rightarrow R_3 = \frac{52}{100} = 0.52$$

Systems Simulation Chapter 7: Random-Number Generation Lechniques for RN Generation Linear Congruential Method

### Linear Congruential Method

Properties to Consider

- Generated numbers must be approximately uniform and independent.
- Moreover, other properties, such as *maximum density* and *maximum period* must be considered.
- By maximum density is meant that the values assumed by  $R_i, i = 1, 2, ...,$  leave no large gaps on [0, 1].
- In many simulation languages, values such as  $m = 2^{31} 1$  and  $m = 2^{48}$  are in common use in generators.
- To help achieve maximum density and to avoid cycling, the generator should have the largest possible period.

### Systems Simulation Chapter 7: Random-Number Generation

Linear Congruential Method

### Linear Congruential Method

Properties to Consider

- For m a power of 2, say m = 2<sup>b</sup>, and c ≠ 0, the longest possible period is P = m = 2<sup>b</sup>, which is achieved whenever c is relatively prime to m (the greatest common factor of c and m is 1) and a = 1 + 4k, where k is an integer.
- For m a power of 2, say m = 2<sup>b</sup>, and c = 0, the longest possible period is P = m/4 = 2<sup>b-2</sup>, which is achieved if the seed X<sub>0</sub> is odd and if the multiplier a, is given by a = 3 + 8k or a = 5 + 8k, for some k = 0, 1, ....
- For m a prime number and c = 0, the longest possible period is P = m 1, which is achieved whenever the multiplier, a, has the property that the smallest integer k such that a<sup>k</sup> 1 is divisible by m is k = m 1.

### Linear Congruential Method

Properties to Consider-Example 1

Using the multiplicative LCM, find the period of the generator for a = 13,  $m = 2^6 = 64$  and  $X_0 = 1, 2, 3, 4$ . When the seed is 1 or 3, the sequence has a period of 16. Period lengths of 8 and 4 is achieved when the seed is 2 and 4, respectively. In this example,  $m = 2^6 = 64$  and c = 0. The max period is then P = m/4 = 16.

Table :	Periods	for	Various	Seeds
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i	Xi	Xi	Xi	Xi
0	1	2	3	4
1	13	26	39	52
2	41	18	59	36
3	21	42	63	20
4	17	34	51	4
5	29	58	23	52
6	57	50	43	36
7	37	10	47	20
8	33	2	35	4

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Linear Congruential Method

### Linear Congruential Method

Properties to Consider-Example 2

With  $a = 13 = 1 + 4 \times k = 1 + 4 \times 3$ , c = 3 is relatively prime to m = 16 and  $X_0 = 1$ , we have the following sequence with the max period of  $P = m = 2^b = 2^4 = 16$ :

#### Table : Max Period

i	Xi	i	Xi
1	0	9	8
2	3	10	11
3	10	11	2
4	5	12	13
5	4	13	12
6	7	14	15
7	14	15	6
8	9	16	1

Systems Simulation Chapter 7: Random-Number Generation — Techniques for RN Generation — Linear Congruential Method

### Linear Congruential Method

Properties to Consider-Example 3

With a = 3, c = 0, prime number m = 17 and  $X_0 = 1$ , we have the following sequence with the max period of P = m - 1 = 16when k = 16 is the smallest integer such that  $a^k - 1 = 3^{16} - 1$ (which equals to 43,046,720) is divisible by k = m - 1 = 16 (verify that for k < 16,  $a^k - 1$  is not divisible by k = m - 1):

i	Xi	i	Xi
1	3	9	14
2	9	10	8
3	10	11	7
4	13	12	4
5	5	13	12
6	15	14	2
7	11	15	6
8	16	16	1

### Systems Simulation Chapter 7: Random-Number Generation

Combined Linear Congruential Method

### Combined Linear Congruential Generators

- A RNG with a period of  $2^{31} 1 \approx 2 \times 10^9$  is no longer adequate due to the increasing complexity. So, combine two or more multiplicative congruential generators in such a way that the combined generator has good statistical properties and a longer period.
- If  $W_{i1}, W_{i2}, \ldots, W_{ik}$  are any independent, discrete-valued RVs (not necessarily identically distributed), but one of them, say  $W_{i1}$ , is uniform on the integers from 0 to  $m_1 2$ , then, the following is uniform on the integers from 0 to  $m_1 2$ .

$$W_i = \left(\sum_{j=1}^k W_{ij}
ight) \mod m_1 - 1$$

#### Combined Linear Congruential Method

### Combined Linear Congruential Generators

• Let  $X_{i1}, X_{i2}, \dots X_{ik}$  be the *i*th output from *k* different multiplicative congruential generators.

$$X_i = \left(\sum_{j=1}^k (-1)^{j-1} X_{ij}
ight) \mod m_1 - 1$$
 $R_i = \left\{egin{array}{c} rac{X_i}{m_1}, & X_i > 0 \ rac{m_1 - 1}{m_1}, & X_i = 0 \end{array}
ight.$ 

• The maximum period is given by  $P = \frac{(m_1-1)(m_2-1)\dots(m_k-1)}{2^{k-1}}$ 

### Systems Simulation Chapter 7: Random-Number Generation $\square$ Techniques for RN Generation

Combined Linear Congruential Method

### Combined Linear Congruential Generators

Algorithm by L'Ecuyer (1998)

Step (1) Select seed  $X_{1,0}$  in the range [1, 2, 147, 483, 562] for the first generator, and seed  $X_{2,0}$  in the range [1, 2, 147, 483, 398] for the second. Set j = 0.

Step (2) Evaluate each individual generator.

$$X_{1,j+1} = 40,014X_{1,j} \mod 2,147,483,563$$
  
 $X_{2,j+1} = 40,692X_{2,j} \mod 2,147,483,399$ 

Step (3) Set

 $X_{j+1} = (X_{1,j+1} - X_{2,j+1}) \mod 2,147,483,562$ 

#### Systems Simulation Chapter 7: Random-Number Generation — Techniques for RN Generation — Combined Linear Congruential Method

Combined Linear Congruential Generators Algorithm by L'Ecuyer (1998)

Step (4) Return

$$R_{j+1} = \begin{cases} \frac{X_{j+1}}{2,147,483,563}, & X_{j+1} > 0\\ \frac{2,147,483,562}{2,147,483,563}, & X_{j+1} = 0 \end{cases}$$

Step (5) Set j = j + 1 and go to step 2.

## Systems Simulation Chapter 7: Random-Number Generation

### **RN** Streams

- The seed for a LCG is the integer value X<sub>0</sub> that initializes the RN sequence.
- Any value in the sequence  $X_0, X_1, \ldots, X_P$  could be used to "seed" the generator.
- A RN *stream* is a convenient way to refer to a starting seed taken from the sequence.
- Typically these starting seeds are far apart in the sequence. If the streams are b values apart, then, stream i could be defined by starting seed S<sub>i</sub> = X<sub>b(i-1)</sub>, for i = 1, 2, ..., [P/b].
- Values of b = 100,000 were common in older generators, but values as large as  $b = 10^{37}$  are in use in modern combined LCGs.

### Tests for RNs

- To check on whether the desirable properties of uniformity and independence, a number of tests can be performed.
- The tests can be placed in two categories, according to the properties of interest: uniformity and independence.
- Frequency Test: Uses the Kolmogorov-Smirnov or the chi-square test o compare the distribution of the set of numbers generated to a uniform distribution.
- Autocorrelation Test: Tests the correlation between numbers and compares the sample compares the sample correlation to the expected correlation, zero.

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#### Tests for RNs

• In testing for uniformity, the hypotheses are as follows:

$$H_0$$
 :  $R_i \sim U[0,1]$   
 $H_1$  :  $R_i \approx U[0,1]$ 

• In testing for uniformity, the hypotheses are as follows:

 $H_0$  :  $R_i \sim$  independently  $H_1$  :  $R_i \sim$  independently

#### Frequency Tests

Kolmogorov-Smirnov (K-S) Test

• This test compared the continuous CDF, F(x), of the uniform distribution with the empirical CDF,  $S_N(x)$ . We have

$$F(x) = x, \quad 0 \le x \le 1$$

- The empirical CDF  $S_N(x)$  defined by  $S_N(x) = \frac{\text{number of } R_1, R_2, \dots, R_N \text{ which are } \leq x}{N}$
- K-S test is based on the largest absolute deviation between  $D = \max |F(x) S_N(x)|$



#### Frequency Tests

K-S Test

- Step (3) Compute  $D = \max(D^+, D^-)$
- Step (4) Locate in Table A.8 the critical value  $D_{\alpha,N}$ .
- Step (5) If  $D > D_{\alpha,N}$ , the null hypothesis is rejected. If  $D \le D_{\alpha,N}$ , conclude that no difference has been detected between the distributions.

### Systems Simulation Chapter 7: Random-Number Generation

Frequency Tests

### Frequency Tests

K-S Test Example

- Suppose that we have five numbers, 0.44, 0.81, 0.14, 0.05 and 0.93. Perform a test for uniformity using the K-S test with the significance level of  $\alpha = 0.05$ .
- We must first rank the numbers from smallest to largest. The calculations are seen in the table on the next slide.
- The computations for  $D^+$  and  $D^-$  are shown as  $i/N R_{(i)}$  and  $R_{(i)} (i-1)/N$ , respectively.
- We see that  $D^+ = 0.26$ ,  $D^- = 0.21$ , D = 0.26 and  $D_{\alpha,N} = 0.565$ . Since  $D < D_{\alpha,N}$ , the hypothesis that the distribution is uniform distribution is not rejected.

Systems Simulation Chapter 7: Random-Numb Tests for RNs Frequency Tests	er Generation	1				
Frequency Tests						
K-S Test Example						
Table	: Calcula	tions fo	r K-S T	est		
$R_{(i)}$	0.05	0.14	0.44	0.81	0.93	
i/Ń	0.20	0.40	0.60	0.80	1.00	
$i/N-R_{(i)}$	0.15	0.26	0.16	-	0.07	
$R_{(i)} - (i-1)/N$	0.05	-	0.04	0.21	0.13	



### **Frequency Tests**

Chi-Square (C-S) Test

• The C-S test uses the sample statistic

$$\chi_0^2 = \sum_{i=1}^n \frac{(O_i - E_i)^2}{E_i}$$

• *O<sub>i</sub>* and *E<sub>i</sub>* are the observed and expected number in class *i*. For equally spaced classes,

$$E_i = \frac{N}{n}$$

• It can be shown that  $\chi_0^2$  is approximately chi-squared distributed with n-1 degrees of freedom.

### Systems Simulation Chapter 7: Random-Number Generation

Frequency Tests

### Frequency Tests

C-S Test Example (Example 7.7 in DESS)

Considering the given data the following computations are done. Since  $\chi^2_0 = 3.4 < \chi^2_{0.05,9} = 16.9$ , the null hypothesis is not rejected.

Table :	Calculations	for	C-S	Test
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Interval	$O_i$	Ei	$O_i - E_i$	$(O_i - E_i)^2$	$\frac{(O_i - E_i)^2}{E_i}$
1	8	10	-2	4	0.4
2	8	10	-2	4	0.4
3	10	10	0	0	0.0
8	14	10	4	16	1.6
9	10	10	0	0	0.0
10	11	10	1	1	0.0
	100	100	0		3.4

#### Autocorrelation Tests

- The tests for autocorrelation are concerned with the dependence between numbers in a sequence.
- We will consider a test for autocorrelation. It requires the computation of autocorrelation between every *m* numbers (*m* is the lag), starting with the *i*th number.
- Thus, the autocorrelation ρ<sub>im</sub> between the following numbers would be of interest: R<sub>i</sub>, R<sub>i+m</sub>, R<sub>i+2m</sub>, ..., R<sub>i+(M+1)m</sub>.
- The value *M* is largest integer st  $i + (M+1)m \le N$ , where *N* is the total number of values in the sequence. We have,

$$H_0 : \rho_{im} = 0$$
$$H_1 : \rho_{im} \neq 0$$

Systems Simulation Chapter 7: Random-Number Generation  $\square$  Tests for RNs

-Autocorrelation Tests

### Autocorrelation Tests

• The distribution of the estimator  $\hat{\rho}_{im}$  is approximately normal if the data are uncorrelated. We have the standard normal test statistic of  $Z_0$  and do not reject  $H_0$  if  $-z_{\alpha/2} \leq Z_0 \leq z_{\alpha/2}$ .

$$Z_{0} = \frac{\widehat{\rho}_{im}}{\sigma_{\widehat{\rho}_{im}}}$$
$$\widehat{\rho}_{im} = \frac{1}{M+1} \left( \sum_{k=0}^{M} [R_{i+km}] [R_{i+(k+1)m}] \right) - 0.25$$
$$\sigma_{\widehat{\rho}_{im}} = \frac{\sqrt{13M+7}}{12(M+1)}$$

Systems Simulation Chapter 7: Random-Number Generation — Tests for RNs — Autocorrelation Tests

### Autocorrelation Tests

Autocorrelation Test Example (Example 7.8 in DESS)

Considering the data in the text, we test for whether the 3rd, 8th, 13th and so on, numbers are autocorrelated using  $\alpha = 0.05$ . Here, i = 3, m = 5, N = 30 and M = 4 (largest integer st  $3 + (M + 1)5 \le 30$ ). Then,

$$\widehat{\rho}_{im} = \frac{1}{M+1} \left( \sum_{k=0}^{M} [R_{i+km}] [R_{i+(k+1)m}] \right) - 0.25$$
  
=  $\frac{1}{4+1} (.23(.28) + .28(.33) + .33(.27) + .27(.05) + .05(.36)) - 0.25$   
=  $-0.1945$ 

Systems Simulation Chapter 7: Random-Number Generation
L Tests for RNs
L Autocorrelation Tests

Autocorrelation Tests

Autocorrelation Test Example (Example 7.8 in DESS)

$$\sigma_{\widehat{\rho}_{im}} = \frac{\sqrt{13M+7}}{12(M+1)} = \frac{\sqrt{13(4)+7}}{12(4+1)} = 0.1280$$
$$Z_0 = \frac{\widehat{\rho}_{im}}{\sigma_{\widehat{\rho}_{im}}} = -\frac{0.1945}{0.1280} = -1.516$$

Since  $-z_{0.025}=-1.96\leq Z_0\leq 1.96=z_{0.025},$  we cannot reject the null hypothesis.

### Summary

- Reading HW: Chapter 7.
- Chapter 7 Exercises.