

#### Batch means method

- Batch means method is used frequently
- Simulation is done as a single (long) run
  - let the length of simulation be M
    - \* here we think that we consider the system from a customer point of view; then M may mean the number of interesting observations (as well we may think that M represents time)
  - let the observed variable be X (for instance, waiting time in a queue) and the task is to estimate its expected value  $\mu = E[X]$
- From the beginning of the simulation, the warm-up period of K observations is rejected
- The useful run (of length M-K) is divided into N batches; thus in each batch there are

$$n = \frac{M - K}{N}$$

observations



# Batch means method (continued)

• In batch i we get for X the sample average  $(X_{ij}$  denotes the  $j^{th}$  observation in the  $i^{th}$  batch)

$$\bar{X}_i = \frac{1}{n} \sum_{j=1}^n X_{ij}$$

• The final estimator for the expectation  $\mu$  is

$$\hat{\mu}_N = \frac{1}{N} \sum_{i=1}^N \bar{X}_i = \frac{1}{nN} \sum_{i=1}^N \sum_{j=1}^n X_{ij}$$

- This is simply the sample average of the whole run (after the warm-up period)
  - the division in batches has no bearing from the point of view of the estimator
  - the sole purpose of the division is to get an idea of the confidence interval of the estimator
- Assuming that the batches are long enough, the sample averages  $\bar{X}_i$  of the batches are approximately independent
- ullet Their sample variance then provides an estimate for the variance of a single  $\bar{X}_i$

$$S^{2} = \frac{1}{N-1} \sum_{i=1}^{N} (\bar{X}_{i} - \hat{\mu}_{N})^{2}$$



# Batch means method (continued)

• The confidence interval of the estimator (at confidence level  $1-\beta$ ) is

$$\hat{\mu}_N \pm z_{1-\beta/2} \frac{S}{\sqrt{N}}$$

- The advantage of the method is that there is only one warm-up period
- There should be at least 20-30 batches in order to estimate the variance reliably
- The bathes should be long enough (much longer than the duration of the initial transient) to guarantee that the  $\bar{X}_i$  are approximately independent
- If there is dependence, the correlation is usually positive
- Then the real confidence interval of  $\hat{\mu}$  is larger than the estimate given above based on the assumption of independent batches
  - the dependence does not at all degrade the value of the estimator
  - it only can mislead the user to believe that the accuracy of the estimator is better than it actually is



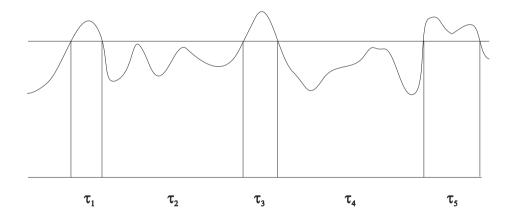
### Regenerative method

- Is applicable in so called regenerative systems
- A regenerative system has at least on regenerative state
  - the stochastic development of the system from tat point on does not at all depend on how this state has been reached
  - every state of a Markovian system is regenerative
  - in an G/G/1 queue the state where the system is empty is a regenerative state
- It there are several regenerative states, one of them is chosen as the basis for the data collection method
  - in the sequel, the regenerative state refers to the chosen regenerative state
- Every now and then the system visits the regenerative state or "regenerates itself"
  - this starts "a new life" which does not depend on the past



# Regenerative method (continued)

- The instant, when the system returns to the regenerative state, is called the regeneration point
- The period between two regeneration points is called the regeneration period
- The developments of different regeneration periods are fully independent of each other
  - this is the "point" of the method





#### Regenerative method: point estimator

- $\bullet$  Let X be the cumulative value of the observed variable during a regenerative period, for instance,
  - the total time the system has spent in a blocking state during a regenerative period
  - the total number of packets overflown from a buffer during the period
- $\bullet$  Let  $\tau$  be the "duration" of the regenerative period
  - this may refer to the real duration (time) of the period
  - it may also refer to e.g. the total number of arrivals during the regenerative period
- The expectation of the observed variable  $\ell$  (for instance, the expectation of time blocking) is

$$\ell = \frac{\mathrm{E}[X]}{\mathrm{E}[\tau]}$$

• In a simulation over n regenerative periods one obtains a (strongly consistent) estimator

$$\bar{\ell}_n = \frac{\bar{X}}{\bar{\tau}}$$

where  $\bar{X}$  and  $\bar{\tau}$  are the sample averages  $\bar{X} = \frac{1}{n} \sum_{i=1}^{n} X_i$  and  $\bar{\tau} = \frac{1}{n} \sum_{i=1}^{n} \tau_i$ 



#### The confidence interval of the estimator

- Consider the variable  $Z_i = X_i \ell \tau_i$ 
  - the  $Z_i$  are independent and identically distributed random variables (with mean 0)
  - so are the  $X_i$  and the  $\tau_i$
- Denote

$$\bar{X} = \frac{1}{n} \sum_{i=1}^{n} X_i, \qquad \bar{\tau} = \frac{1}{n} \sum_{i=1}^{n} \tau_i, \qquad \bar{Z} = \frac{1}{n} \sum_{i=1}^{n} Z_i = \bar{X} - \ell \bar{\tau}$$

• By the central limit theorem we have

$$\frac{n^{1/2}\bar{Z}}{\sigma} = \frac{n^{1/2}(\bar{X} - \ell\bar{\tau})}{\sigma} \to N(0, 1), \quad \text{kun } n \to \infty$$

where  $\sigma^2$  is the variance of Z

$$\sigma^2 = V[Z] = V[X] - 2\ell Cov[X, \tau] + \ell^2 V[\tau]$$



# The confidence interval of the estimator (continued)

• By dividing by  $\bar{\tau}$  we get

$$\frac{n^{1/2}(\bar{\ell}_n - \ell)}{\sigma/\bar{\tau}} \to N(0, 1), \text{ when } n \to \infty$$

• For the point estimator  $\bar{\ell}_n$  based on measurement over n regenerative periods we get the confidence interval (at the confidence level  $1-\beta$ )

$$\bar{\ell}_n \pm \frac{z_{1-\beta/2}S}{\sqrt{n}\bar{\tau}}$$

where  $S^2$  is the (unbiased) estimator of  $\sigma^2$  based on the sample

$$S^2 = S_{11} - 2\,\bar{\ell}_n\,S_{12} + \bar{\ell}_n^2\,S_{22}$$

and  $S_{11}$ ,  $S_{22}$  and  $S_{12}$  are the sample variances and sample covariance of X and  $\tau$ 

$$S_{11} = \frac{1}{n-1} \sum_{i=1}^{n} (X_i - \bar{X})^2, \quad S_{22} = \frac{1}{n-1} \sum_{i=1}^{n} (\tau_i - \bar{\tau})^2, \quad S_{12} = \frac{1}{n-1} \sum_{i=1}^{n} (X_i - \bar{X})(\tau_i - \bar{\tau})$$



#### Regenerative method: discussion

- Advantages
  - separate transient removal is not needed
  - one does not have to fix parameters such as the number of batches in advance
  - asymptotically accurate
  - easy to understand and implement
- There are, however, a few disadvantages
  - it may be difficult to identify regenerative states
  - even if one can be identified
    - \* the regenerative period may be very long (the user has no control over it)
    - \* in a complex system the identification of the regenerative state may be computationally expensive
  - with a finite value of n the estimator  $\bar{\ell}_n$  is biased
    - \* in fact, the initial transient problem does exist, though it is somewhat concealed