

# Simulations

Homework 7

M.S. in Stochastics and Data Science

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## 1 Exercise 1

### 1.1 Overview

We start this discussion by taking a look at the main characteristics of the network of queues in question.

In this system we have  $N = 10$  machines departing from the “delay station”  $Z$  with a certain rate (which is modeled by a random variable  $Z$ ); from here they reach a short repair station where they undergo a short reparation whose duration is another random variable  $X$ ; finally, with a probability  $\beta = 0.2$  they reach a long repair station where the duration of the repair is yet another random variable  $Y$ . The machines that do not go to the long repair station or that have finished the long repair go back to the source. In this case the distribution of all the three stations is **negative exponential distributions**:

$$F_X(x) = \mathbb{P}(X \leq x) = 1 - e^{-\frac{1}{\eta}x} \quad f_X(x) = \frac{dF_X}{dx} = \lambda e^{-\frac{1}{\eta}x}.$$

In this formulation the parameter is given directly as the expected value  $\mathbb{E}[X] = \eta$  of the distribution. We have our three expected values, reflecting the average time of each of these three events:

- ① time between breakages of a machine:  $\eta_{\text{arrival}} = 3000$  mins;
- ② service time of the short repair station:  $\eta_{\text{short}} = 40$  mins;
- ③ service time of the long repair station:  $\eta_{\text{long}} = 960$  mins.

This characteristic brings us to the particular case of the tandem server with “M/M/2” service and arrival times seen during lectures. In this scenario, due to the memoryless property of the negative exponential distribution for all time variables (e.g., failure times, short and long repair times), defining regeneration points is straightforward. For example, a regeneration point can be set as the time when a machine enters the long repair station and the system resets to its initial conditions. This choice is based on the following schema:

Service time distribution of the first queue	Service time distribution of the second queue	
	GENERIC	MARKOV (Neg-Exp)
GENERIC	Any departure that leaves behind exactly $N - 1$ customers from one of the two servers of the network	Any departure from the first server
MARKOV (Neg-Exp)	Any departure from the second server	Any departure in the system

**Tabella 1:** Service time distribution schema for the first and second queue.

in which we can easily notice we are in the bottom-right case, in which the service times of both the queue are negative-exponential.

Technically every departure could be a regeneration point but since our analysis focuses on the average waiting time of the long repair station we chose as regeneration points all the departures from the long station. This choice will also simplify our calculations: the value  $\nu_j$ , that counts the number of the occurrences of the event of interest in the current regeneration cycle, will always be 1.

For the distribution of the routings we assume a uniform distribution (so that 20% of the departures from the short station will become an arrival to the long station).

## 1.2 The simulation

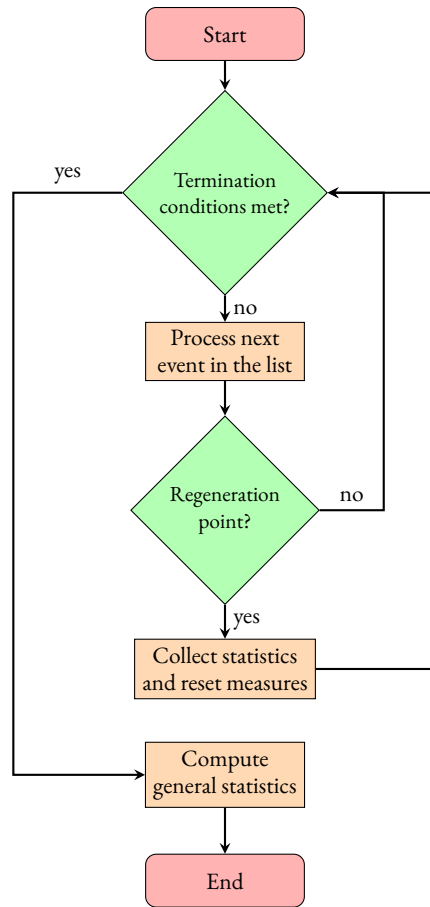
For the implementation of this simulation we chose the classic event list approach: the bulk of the simulator is an ever-growing list of events sorted by the timestamp of their occurrence. Each of these events is “processed” one by one, typically by adding another related event to the list and computing the necessary measurements.

To implement the regeneration method, we will keep track of the measurements of interest for each cycle  $j$  (like the total waiting time at a certain station  $A_j$  and the count  $\nu_j$  of events happened during that cycle) and once we meet a regeneration point we accumulate those measures in global cumulative variables before resetting them and starting over. First of all, we define a structure to handle each entry of our event list:

```

1 typedef struct Event {
2     int machine; // this will identify what machine we are talking about.
3     char type;   // 'A' for Arrival, 'S' for Departure (Short Station), 'L'
4                 // for
5                 // Departure (Long Station)
6     double timestamp; // The time the event occurs
7 } Event;
```

By doing this we can always keep track of the information of each event that will help us determine what will happen next. We then initialize our event list.



**Figura 1:** Flowchart of the operations of our simulator.

```

1  Event *event_list = NULL; // Pointer to the array of events
2  size_t event_count = 0;   // Number of events currently in the list. This
    will
3  // grow as we add more events.
4  size_t event_capacity =
5  0; // This is how much memory we have allocated for this array. When the
6  // list is full we need to realloc an expanded version of this array.

```

We are going to use a dynamic array which whose size we are going to increase whenever needed. Each time we want to add an element to our event list we call this function:

```

1  void add_event(Event new_event) {
2  // Check if resizing is needed
3  if (event_count == event_capacity) {
4      size_t old_capacity = event_capacity;
5      event_capacity = (event_capacity == 0) ? 10 : event_capacity * 2;
6      Event *temp_list = realloc(event_list, event_capacity * sizeof(Event
7      ));
8      if (!temp_list) {

```

```

8         fprintf(stderr, "Memory allocation failed!\n");
9         exit(EXIT_FAILURE);
10    }
11    event_list = temp_list;
12
13    // Initialize the newly allocated memory
14    for (size_t i = old_capacity; i < event_capacity; i++) {
15        event_list[i].machine = 0;
16        event_list[i].type = '\0';
17        event_list[i].timestamp = 0.0f;
18    }
19 }
20
21 // Add the new event to the list (temporarily at the end)
22 event_count++;
23 event_list[event_count - 1] = new_event;
24
25 // Sort the event list (insertion sort)
26 size_t i = event_count - 1;
27 while (i > 0 && event_list[i - 1].timestamp > event_list[i].timestamp) {
28     Event temp = event_list[i];
29     event_list[i] = event_list[i - 1];
30     event_list[i - 1] = temp;
31     i--;
32 }
33 }

```

Here the first chunk of the code handles the dynamic resizing of the array to take into account new events added to the event list and initializes the new placeholder events; the second half of the code inserts the event at the end of the list and then performs an insertion sort to ensure the event reaches its correct placement inside the event list. This allows us to know that after inserting an event the event list will always be correctly ordered.

Before going to the engine of the simulation, we define some helper functions:

```

1 int RegPoint(Event current_event) {
2     // Regeneration point occurs at a S or L event
3     // Returns 1 (true) for regeneration point, 0 (false) otherwise
4     return (current_event.type == 'L');
5 }

```

This is a simple function that checks whether the event that we are processing is a regeneration point. In this case it is quite an easy call, since all 'L' (departure from long repair station) events are regeneration points.

```

1 void CollectRegStatistics(double *wait_currentcycle_short_station,
2 double *wait_currentcycle_long_station,
3 double *accumulated_wait_short,
4 double *accumulated_wait_long, int *cycle_count) {
5     *accumulated_wait_short +=
6     *wait_currentcycle_short_station; // Accumulate waiting time for short
7     // station

```

```

8      *accumulated_wait_long +=
9      *wait_currentcycle_long_station; // Accumulate waiting time for short
10     // station
11     (*cycle_count)++;                // Increment the cycle count
12 }

```

After encountering a regeneration point, this function collects the cycle-specific measures `wait_currentcycle_short_station` (which is the cumulative waiting time during cycle  $j$  at the short repair station) and `wait_currentcycle_long_station` (similarly, the waiting time at the long repair station during cycle  $j$ ) into global accumulators for later computations. Moreover, this function is also responsible to increase the counter of how many cycle have passed.

```

1 void ResetMeasures(double *wait_currentcycle_long_station,
2 double *wait_currentcycle_short_station) {
3     *wait_currentcycle_short_station =
4     0.0; // Reset the cycle-specific waiting time
5     *wait_currentcycle_long_station =
6     0.0; // Reset the cycle-specific waiting time
7 }

```

This function simply resets the cycle-specific measure we talked about before.

```

1 int DecideToStop(int cycle_count, double error_percentage, int iteration_number
2 ) {
3     return ((cycle_count>40 && error_percentage<0.10) || iteration_number>
4             MAX_EVENTS);
5 }

```

This is another simple functions like `RegPoint` that checks whether the termination conditions are reached. In our case, we decided to continue the simulation until one of these two conditions is reached:

1. we surpass 40 cycles (so that we find ourselves in a setting in which the T-statistic converges towards the normal distribution) and our error is less than 10% of our point estimate for the mean waiting time at the long station;
2. we surpass an arbitrary threshold `MAX_EVENTS` to avoid the code to execute itself ad infinitum.

```

1 double ComputeConfidenceIntervals(double mean_wait_long, double
2 time_events_product_long, double L_event_count, double
3 accumulated_wait_long_squared, int cycle_count) {
4     double S_A=accumulated_wait_long;
5     double S_nu=L_event_count;
6     double S_AA=accumulated_wait_long_squared;
7     double S_Anu=time_events_product_long;
8     double S_nunu=L_event_count; // every cycle has nu=1 so the sum of the
9     squared nu is just the event count
10    double r_hat=S_A/S_nu;
11    double delta = sqrt(cycle_count/(cycle_count-1)) * (sqrt(S_AA-2*r_hat*S_Anu
12    +pow(r_hat,2)*S_nunu)/S_nu);

```

```

9     double error = 1.96*delta;
10    //printf("Error=%f\n",error);
11    return error;
12 }

```

This function computes the confidence intervals for the point estimator of the average waiting time at the long station  $\hat{r}$ . Remember that the confidence interval at the level  $(1 - \alpha)$  for  $r$  can be expressed as

$$\hat{r} - t_{p-1, \alpha/2} \Delta \leq r \leq \hat{r} + t_{p-1, \alpha/2} \Delta$$

where

$$p = \text{number of regeneration cycles}$$

$$\Delta = \frac{\hat{s}_Z}{\bar{\nu} \sqrt{p}}.$$

where  $\hat{s}_Z^2$  is the sample standard deviation of the auxiliary variable  $Z_j = A_j - r\nu_j$  (used to construct the random variable  $\frac{\bar{Z}}{\sigma_Z/\sqrt{p}} \sim \mathcal{N}(0, 1)$ ) and  $\bar{\nu}$  is the average number of occurrences of the event of interest in each cycle  $\frac{1}{n} \sum_{j=1}^n \nu_j$  (that in our case, since  $\nu_j = 1 \forall j$  by design, will always be equal the the number of cycles).

Luckily, we do not have to keep track of each single waiting time or occurrence count, since we know that we can express  $\Delta$  as

$$\Delta = \sqrt{\frac{p}{p-1}} \cdot \frac{\sqrt{\hat{S}_{AA} - 2\hat{r}\hat{S}_{A\nu} + \hat{r}^2\hat{S}_{\nu\nu}}}{\hat{S}_\nu}$$

where

$$\hat{S}_{AA} = \sum_{j=1}^p A_j^2$$

$$\hat{S}_{A\nu} = \sum_{j=1}^p A_j \nu_j$$

$$\hat{S}_{\nu\nu} = \sum_{j=1}^p \nu_j^2$$

$$\hat{S}_\nu = \sum_{j=1}^p \nu_j$$

which are all quantities we can easily accumulate each time we process an event. Moreover, since by design we always go further 40 cycles, we can ditch the T-statistic and directly use the (bi-lateral) 95%

quantile from the normal standard distribution  $-z_{0.05/2} = 1.96$ . So, in the end, we will have that

$$\mathbb{P} \left( \hat{r} - 1.96 \cdot \sqrt{\frac{p}{p-1}} \cdot \frac{\sqrt{\hat{S}_{AA} - 2\hat{r}\hat{S}_{Av} + \hat{r}^2\hat{S}_{vv}}}{\hat{S}_v} \leq r \leq \hat{r} + 1.96 \cdot \sqrt{\frac{p}{p-1}} \cdot \frac{\sqrt{\hat{S}_{AA} - 2\hat{r}\hat{S}_{Av} + \hat{r}^2\hat{S}_{vv}}}{\hat{S}_v} \right) \approx (1 - \alpha) = 0.95.$$

We also need a way to generate our exponential random variable. Since we explicitly know the formula of the cumulative distribution function of the exponential distribution, we can use the **inverse transformation method** to transform uniform random variables into exponential random variables. In this case, if  $X \sim \text{Exp}(\eta)$  then we can compute the inverse distribution function by solving the cumulative distribution function for  $x$ :

$$x = F^{-1}(u) = -\eta \ln(1 - u) \quad 0 < u < 1.$$

So choosing  $u \sim \text{Unif}(0, 1)$  and plugging it into the inverse distribution function we can obtain a random variable that is drawn from the exponential distribution.

```

1 double exponential_random(double heta) {
2     double unif = (double)rand() / RAND_MAX;
3     if ((1 - unif) < 1e-20) {
4         unif = 1e-20; // this will give us a limit in the case in which the
5                         // argument
6                         // of the logarithm is too close to 0 (and thus exploding)
7     }
8     double exp = (-heta * logf(1 - unif));
9     // double pick = 1 - ((double)rand() / RAND_MAX);
10    verbose ? printf("This time I extracted %f!\n", exp) : 0;
11    return exp;
12 }
```

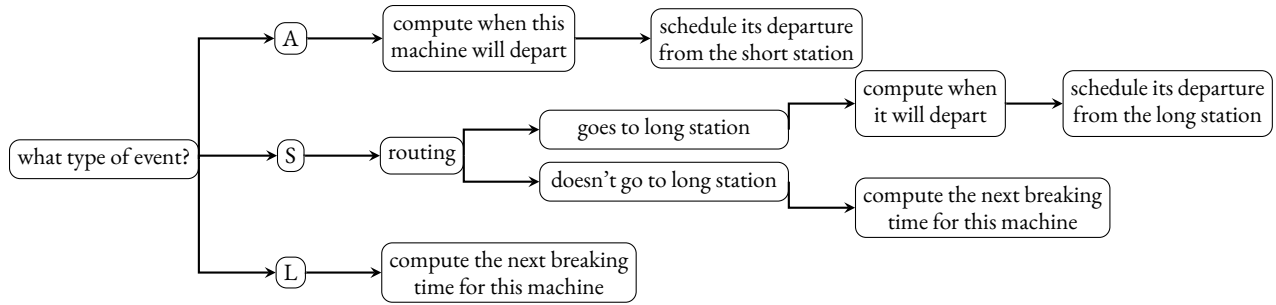
Here we needed to take a little safety measure since drawing uniform samples very close to 1 would sometimes cause the logarithm to explode to  $\infty$ . By enforcing a lower bound we may lose some accuracy in our model but at least we don't end up with infinity values.

Now we are ready to tackle the main engine of the simulator, which is the `process_event` function. We thought about this function as cursor that traverses the event list item by item and schedules one or more event according to what type of event we are processing and which machine is involved. So, in detail, the following operations will be done.

#### ① The event processed is a 'A' event (arrival at the short repair station):

- We compute when this machine will depart from the short repair station.
  - (a) if the queue of the short repair station is empty, then its departure time will simply be
 

time of arrival + random service time;



**Figure 2:** Schematics of the engine workflow.

- (b) if the queue is not empty, we fetch the departure time of the last machine in the queue and then the departure time from the short repair station of the machine whose event we are processing will be

latest time of departure of the queue + random service time;

- Add in the event list the newly computed event, which will be of type 'S' and will belong to the same machine whose arrival we are processing.

② **The event processed is a 'S' event (departure from a short repair station):**

- We toss a coin to determine, with a probability of  $\beta = 0.2$ , whether the machine will be sent to the long repair station.

(a) If the machine *gets sent to the long repair station*:

- i. We compute when this machine will depart from the long repair station.

A. if the queue of the long repair station is empty, then its departure time will simply be

time of arrival + random service time;

B. if the queue is not empty, we fetch the departure time of the last machine in the queue and then the departure time from the long repair station of the machine whose event we are processing will be

latest time of departure of the queue + random service time;

- ii. Add in the event list the newly computed event, which will be of type 'L' and will belong to the same machine whose arrival we are processing.

(b) If the machine *does not get sent to the long repair station*:

- i. Compute its next breaking time (and consequent arrival to the short repair station), which will be:

time of departure from the short station + random time

- ii. Add in the event list the newly computed event, which will be of type 'A' and will belong to the same machine whose arrival we are processing.



### ③ The event processed is a 'L' event (departure from a long repair station):

- Compute its next breaking time (and consequent arrival to the short repair station), which will be:  
$$\text{time of departure from the long station} + \text{random time}$$
- Add in the event list the newly computed event, which will be of type 'A' and will belong to the same machine whose arrival we are processing.

This nested list should give the idea of how the `process_event` has been designed. Of course, if the event is of the type 'L' (a regeneration point), the function also calls the helper functions whose job consists in accumulating and resetting the measurements along with the regeneration cycle. Here is the code for such function:

```
1 void process_event(Event current_event, int pos) {
2     // start by doing the task of verifying whether the event is a
3     // regeneration
4     // point if it is, then collect the statistics.
5     if (RegPoint(current_event)) {
6         /* we accumulate the number of L events in a global accumulator.
7         Of course, this means that each cycle j will have \nu_j=1 event
8         count, since
9         we always regenerate at the first L event found. This will be used
10        to
11        compute the point estimate of the waiting time.
12        */
13        L_event_count++;
14        CollectRegStatistics(&wait_currentcycle_short_station,
15        &wait_currentcycle_long_station,
16        &accumulated_wait_short, &accumulated_wait_long,
17        &cycle_count); // collect statistics
18        ResetMeasures(&wait_currentcycle_long_station,
19        &wait_currentcycle_short_station);
20
21        verbose ? printf("I found event of type %c, which is a regeneration
22        point. "
23        "I cleaned statistics and accumulated what I had to "
24        "accumulate.\n\n",
25        current_event.type)
26        : 0;
27    }
```

Before doing anything else, the function checks whether the event is a regeneration point and accumulates and resets the measurements accordingly. Then it starts processing the event based on its type

```
1     // Process the event depending on its type
2     verbose ? printf("Now processing: %c event of machine %d, number %d in
3     the "
4     "event list, at "
5     "time %f.\n",
```

```

5    current_event.type, current_event.machine, pos,
6    current_event.timestamp)
7    : 0;
8    if (current_event.type == 'A') {
9        // we compute when this machine will depart.
10       // we must check the case in which the queue is empty and in which
11       // it isn't.
12       // remember, we start from the "pos" position an empty queue means
13       // that
14       // there are no departure events ahead of our current event.
15       // We don't care about what machine is departing, the order will be
16       // scrambled anyway
17       double last_departure_timestamp = -1.0;
18       // if we do not find any 'S' events out timestamp will remain -1.0
19       // and
20       // that's how we will know that there are no S events scheduled
21       // ahead of our
22       // current event
23       for (size_t i = pos; i < event_count; i++) {
24         if (event_list[i].type == 'S') {
25             last_departure_timestamp = event_list[i].timestamp;
26         }
27     }
28     // now we create and insert the departure of the current event. This
29     // event
30     // will always be about the same machine of the
31     Event current_departure;
32     current_departure.type = 'S';
33     current_departure.machine = current_event.machine;
34     if (last_departure_timestamp == -1.0) {
35         current_departure.timestamp =
36             current_event.timestamp +
37             exponential_random(heta_short); // empty queue
38         verbose ? printf("Wow, no one in queue! ") : 0;
39     } else {
40         current_departure.timestamp =
41             last_departure_timestamp +
42             exponential_random(heta_short); // someone in the queue
43     }
44     // insert the event
45     add_event(current_departure);
46     verbose ? printf("Added the departure event %c of the machine "
47                     "%d(corresponding to our "
48                     "current event %d) at time %f\n",
49                     current_departure.type, current_departure.machine, pos,
50                     current_departure.timestamp)
51     : 0;
52
53     /* compute the waiting time for this current event (which IS AN
54        ARRIVAL, but we know its departure now!).
55        we also need to compute the square and accumulate it in another

```

```

50     variable.
51     we will need it to compute the sample variance! */
52     double waiting_time_short = current_departure.timestamp -
53         current_event.timestamp;
54     double waiting_time_short_squared = pow(waiting_time_short, 2);
55     wait_currentcycle_short_station += waiting_time_short;
56     accumulated_wait_short_squared += waiting_time_short_squared;
57     time_events_product_short += waiting_time_short*1;

```

We store the cumulative waiting times for this cycle in the variable `wait_currentcycle_short_station`. We accumulate also the squares of the waiting times (that we will use for the interval estimation) and the product between times and event count (which is equal to `wait_currentcycle_short_station` since in this simulation  $\nu_j$  is always 1 by design).

To check whether the queue is empty or not we start with a “sentinel” variable `last_departure_timestamp` equal to -1.0 (a timestamp that we are sure no other event in the list could ever have) and then we start checking the events in the event list (which is always sorted in the right way!) following the current event searching for other departures from the short repair station. Every time we find a departure we write in `last_departure_timestamp` its timestamp until we reach the end of the list. If by that time `last_departure_timestamp` is still =-1.0 then we know that there are no other machines with scheduled departure in the future (and therefore the queue is empty). Otherwise we already have the timestamp that we are interested in to compute the departure of the current arrival.

In the end, we add the event to the list.

```

1     } else if (current_event.type == 'S') {
2
3         /*
4         Things get trickier: we have two scenarios when processing an S-
5         event.
6         If we do not go to the L station then our machine comes back to the
7         pool and
8         we can schedule its next departure. Otherwise... we need to send it
9         to long
10        repair, where something similar will happen.
11        */
12
13        double last_departure_timestamp = -1.0; // sentinel reset!
14        // first, we decide whether this event is going to the long repair
15        station
16        // or not
17        double coin_flip = (rand() / (double)RAND_MAX);
18        if (coin_flip <= beta) {
19            verbose ? printf("Bad luck, machine %d! You get a long repair!\n",
20                current_event.machine)
21                : 0;
22            // go to the long station and schedule the departure event
23            Event current_departure_long;
24            current_departure_long.type = 'L';

```

```

21     current_departure_long.machine = current_event.machine;
22     // do the same thing as before
23     for (size_t i = pos; i < event_count; i++) {
24         if (event_list[i].type == 'L') {
25             last_departure_timestamp = event_list[i].timestamp;
26         }
27     }
28     // we got our sentinel
29     if (last_departure_timestamp == -1.0) {
30         current_departure_long.timestamp =
31         current_event.timestamp +
32         exponential_random(heta_long); // empty queue
33         verbose
34         ? printf(
35             "But at least there was no one in queue for the long
              station")
36           : 0;
37     } else {
38         current_departure_long.timestamp =
39         last_departure_timestamp +
40         exponential_random(heta_long); // someone in the queue
41     }
42     // insert the event
43     add_event(current_departure_long);
44     verbose
45     ? printf("\nAdded departure event %c for machine %d at time %f\n",
              current_departure_long.type, current_departure_long.machine,
              current_departure_long.timestamp)
46       : 0;
47
48     /*
49     now we have scheduled the departure from the long station;
50     we are now to calculate the waiting time for this machine
51     to exit the long station
52     */
53     double waiting_time_long = current_departure_long.timestamp -
54     current_event.timestamp;
55     double waiting_time_long_squared = pow(waiting_time_long, 2);
56     wait_currentcycle_long_station += waiting_time_long;
57     accumulated_wait_long_squared += waiting_time_long_squared;
58     time_events_product_long += waiting_time_long * 1;
59 } else {
60     // the machine goes back to the source and we schedule its next
61     arrival to
62     // the short station.
63     Event next_arrival_for_this_machine;
64     next_arrival_for_this_machine.type = 'A';
65     next_arrival_for_this_machine.machine = current_event.machine;
66     next_arrival_for_this_machine.timestamp =
67     current_event.timestamp + exponential_random(heta_arrival);

```

```

68         add_event(next_arrival_for_this_machine);
69         verbose ? printf("The machine %d gets back to the source. It
           will break "
70         "again at time %f\n",
71         next_arrival_for_this_machine.machine,
72         next_arrival_for_this_machine.timestamp)
73         : 0;
74     }

```

We treat the 'S' events as we said before, by tossing a coin and performing the corresponding operations.

```

1     } else if (current_event.type == 'L') {
2         // the machine goes back to the source. Schedule its next arrival!
3         Event next_arrival_after_long;
4         next_arrival_after_long.type = 'A';
5         next_arrival_after_long.machine = current_event.machine;
6         next_arrival_after_long.timestamp =
7         current_event.timestamp + exponential_random(heta_arrival);
8         add_event(next_arrival_after_long);
9         verbose ? printf("Found a L event. Scheduled next arrival for this
           machine "
10        "%d that will break again at time %f\n",
11        next_arrival_after_long.machine,
12        next_arrival_after_long.timestamp)
13        : 0;
14    }
15    verbose ? printf("Done processing event %c regarding machine %d, number %
           d "
16    "in the list, at time %f. \n",
17    current_event.type, current_event.machine, pos,
18    current_event.timestamp)
19    : 0;
20    verbose ? printf("-----\n\n")
21    : 0;
21 }

```

The last section of the function handles the 'L' events in a similar manner.

Now that we have the engine of the simulator we are ready to analyze the main function of the program.

```

1 int main(int argc, char *argv[]) {
2
3     clock_t start_time = clock(); // start the stopwatch
4
5     for (int i = 1; i < argc; i++) {
6         if (argv[i][0] == '-' && argv[i][1] == 'v') {
7             verbose = 1; // Enable verbose logging
8             break;       // No need to check further once we find the flag
9         }
10    }

```

We gave to the main function the possibility to be called with a `-v` argument that enables (very) verbose logging. This logging allows to follow the simulation event by event by seeing each element of the event list, its order in the list, how it gets processed, whether it is a regeneration point and what happens next. Of course, this slows down the execution time (which is being tracked here) to a great extent.

```
1 // more initializations
2 srand(time(NULL)); // Seed the random number
  generator
3 event_list = malloc(10 * sizeof(Event)); // Initial allocation for 10
  events
4 event_capacity = 10;
5 if (!event_list) {
6     fprintf(stderr, "Memory allocation failed...\n");
7     exit(EXIT_FAILURE);
8 }
```

Here we choose a seed based on the processor's time, we initialize the event list and we allocate the memory for the dynamic array.

```
1 // Create and add the first arrival event for each machine
2 for (int i = 1; i <= n; i++) {
3     Event first_event;
4     first_event.machine = i;
5     first_event.type = 'A';
6     first_event.timestamp = exponential_random(heta_arrival);
7     add_event(first_event);
8 }
9
10 // now we have all the first arrivals for each machine. What we need to
   do is
11 // scale all of these events to start from 0 because
12 double delta = event_list[0].timestamp;
13 event_list[0].timestamp = 0;
14 for (int i = 1; i < n; i++) {
15     int temp = event_list[i].timestamp;
16     event_list[i].timestamp = temp - delta;
17 }
```

We then proceed to initialize the event list. We choose  $N = 10$  different arrival times for the first arrivals, we add them to the event list and then we scale them all so that the first timestamp is equal to 0.0. We now start to process, one by one, the event of the list. Of course, after processing one event the event list will be changed and to the order of execution. The processing keeps being executed in strict chronological order until one of the conditions stated in `DecideToStop` becomes true.

```
1 // now the main loop. we need to iterate for each element of the event
  list,
2 // which will grow forever if we don't stop it!.
3 int i = 0;
```

```

4     do {
5         Event current_event = event_list[i];
6         process_event(current_event, i);
7         if (isinf(current_event.timestamp)) {
8             printf("Timestamp reached infinity. Stopping the loop.
9                 Something is wrong.\n");
10            break; // Exit the loop immediately
11        }
12        // Now calculate our point estimator
13        mean_wait_long = accumulated_wait_long / L_event_count;
14        // Calculate the confidence intervals
15        if(cycle_count>1){
16            error = ComputeConfidenceIntervals(mean_wait_long,
17                time_events_product_long, L_event_count,
18                accumulated_wait_long_squared, cycle_count);
19            error_percentage = 2*error/mean_wait_long;
20        }
21        iteration_number++;
22        i++;
23    } while (!DecideToStop(cycle_count,error_percentage,iteration_number));
24    printf("Stopping conditions reached at the %d-th iteration",
25        iteration_number);

```

Since one of the conditions we imposed was that the error interval should be at most 10% of the point estimate for the mean waiting time at the long repair station, we must calculate the error interval at any iteration of the loop.

```

1     // Capture the end time
2     clock_t end_time = clock();
3
4     // Calculate the time taken and print it
5     double sim_duration = (double)(end_time - start_time) / CLOCKS_PER_SEC;
6
7
8
9     printf("\n_____ \n");
10    printf("Simulation complete! :) ");
11    printf("Execution time: %f seconds\n", sim_duration);
12    printf("Total cycles: %d.\n", cycle_count);
13    printf("Average waiting time for the long station: %f\n",
14        mean_wait_long);
15    printf("Confidence interval at 10%%: (%f,%f).\n", mean_wait_long-error,
16        mean_wait_long+error);
17    printf("The error is the %f%% of the point estimate.\n", error_percentage
18        *100);
19
20    // Cleanup allocated memory
21    cleanup_event_list();
22
23    return 0;
24 }

```

---

We end the function with the printing of the results and the cleanup of the allocated memory. After an execution, a typical (non verbose) log will look like this:

```
Stopping conditions reached at the 14507-th iteration
```

---

```
Simulation complete! :) Execution time: 0.003000 seconds
Total cycles: 1313.
Average waiting time for the long station: 1808.140007
Confidence interval at 10%: (1717.798290,1898.481723).
The error is the 9.992779% of the point estimate.
```

The average waiting time still suffers from some variability (the sample mean of a random variable is still a random variable in itself!), but the confidence interval most of the times includes the expected value of 1811.030708 minutes. If we let the simulation run for longer times (for example by letting the simulator iterate until the MAX\_EVENT number of iterations is reached) the average waiting time gets closer and closer to the numerically derived value.

## 2 Exercise 2

### 2.1 Overview

In this exercise we keep the main bulk of the simulator and we switch the distribution of the long service times with an hyper-exponential distribution:

$$f_X(x) = \alpha_1 \cdot \frac{1}{\mu_1} \cdot e^{-\frac{x}{\mu_1}} + \alpha_2 \cdot \frac{1}{\mu_2} \cdot e^{-\frac{x}{\mu_2}}.$$

This is a *mixture distribution* made by different exponential components, each with its weights. Sampling from this What about the regeneration point? According to the table 1 we are now in the case with a first Markovian/Exponential queue and a second generic distribution queue. This means that *any departure from the second server* is a valid regeneration point, so we can keep our occurrence of 'L' events as our regeneration point.

Extracting variables from a hyper-exponential distribution is not particularly hard. We are going to reuse the `exponential_random` function inside our code.

```
1
2 double hyperexponential_random(int k, double* alpha, double* heta) {
3     // Cumulative distribution for alpha
4     double cumulative_alpha[k];
5     cumulative_alpha[0] = alpha[0];
6     // Simply add all the alphas parameter (they sum to 1)
7     for (int i = 1; i < k; i++) {
8         cumulative_alpha[i] = cumulative_alpha[i - 1] + alpha[i];
9     }
```



```

10
11 // Generate a uniform random number
12 double Y = (double)rand() / RAND_MAX;
13
14 // Select the component distribution: find which distribution
    corresponds has a cumulative probability that corresponds to the
    drawn uniform variable
15 int j = 0;
16 while (Y > cumulative_alpha[j]) {
17     j++;
18 }
19
20 // Generate a random variable from the chosen exponential distribution
21 double X = exponential_random(heta[j]);
22
23 return X;
24 }

```

The main mechanism here lies in the fact that the random variable  $Y \sim \text{Unif}(0, 1)$  finds which exponential distribution (in this case, out of 2) we must draw the random number from. In this case our parameters are:

- $\mu_1 = 10$  mins with weight  $\alpha_1 = 0.95$ ;
- $\mu_2 = 19010$  mins with weight  $\alpha_1 = 0.05$ .

The expected value of the hyperexponential distribution is straightforward to compute: when we have  $X \sim \text{HyperExp}(\alpha, \mu)$ , then

$$\mathbb{E}[X] = \sum_{i=1}^k \alpha_i \eta_i.$$

In this case, given our parameters, we will have

$$\mathbb{E}[X] = 0.95 \cdot 10 + 0.05 \cdot 19010 = 960 \text{ mins.}$$

The expected value of the distribution of the times of the long station is the same both in this case and in the previous exercise.

## 2.2 The Mean Value Analysis

Before trying to simulate the behavior of the system with this modification, we can use our Mean Value Analysis (“MVA\_LI&D”) code from the homework 4 to have a numerical idea of what we should expect.

The MVA can provide measures for average waiting times, throughput and utilizations for a closed system with both load independent and delay stations. The difference, in our case, is that the arrival and service times are not anymore fixed quantities but rather random variables; since MVA is based

on averages, though, we can do a little tweak of the system by substituting each random variable with its expected value. This allows us to feed into the MVA algorithm a system with the following parameters:

- $M = 3$  stations;
- $N = 10$  customers in the system;
- time of output of the delay station  $Z = 3000$  mins (we can imagine, since all machines break in the same moment in this scenario, that they leave the delay station sequentially);
- routing matrix

$$\begin{bmatrix} 0 & 1 & 0 \\ 0.8 & 0 & 0.2 \\ 1 & 0 & 0 \end{bmatrix};$$

- service time of the short repair station  $S_1 = 40$  mins;
- service time of the long repair station  $S_2 = 960$  mins.

As we see here, since both the exponential and the hyper-exponential distributions have the same expected value of 960 mins, the MVA procedure makes no difference between them. Here is the code of the MVA analysis (taken from our previous homework):

```

1  #include <stdio.h>
2
3  // Constants
4  #define M 3      // Number of stations
5  #define N 10     // Maximum number of customers
6
7  // Input parameters
8  double Z = 3000; // Delay time of the station
9  double S[M] = {0, 40, 0.95*10+0.05*19010}; // Service times
10 char ST[M] = {'D', 'L', 'L'}; // Station types ('L' for load independent, 'D'
    for delay. Our reference station is the delay)
11 double Q[M][M] = {
12     {0, 1, 0},
13     {0.8, 0, 0.2},
14     {1, 0, 0}
15 };
16
17 double V[M];
18
19 // We need bi-dimensional arrays for results
20 double X[M][N+1];
21 double U[M][N+1];
22 double n[M][N+1];
23 double w[M][N+1];
24 double R[M][N+1];
25

```

```

26 int main() {
27     // Initialization
28     for (int i = 0; i < M; i++) {
29         n[i][0] = 0.0; // put 0 as the value for all stations
30     }
31
32     // Compute visit count
33     V[0]=1.0;
34     V[1]=V[0]/Q[0][1];
35     V[2]=V[1]*Q[1][2];
36
37     // Compute performance measures for each population size k (from 1 to N)
38     for (int k = 1; k <= N; k++) {
39
40         // Compute the waiting time w_i[k] for each station i
41         for (int i = 0; i < M; i++) {
42             if (ST[i] == 'D') {
43                 w[i][k] = Z; // Delay station
44             } else {
45                 w[i][k] = S[i] * (1 + n[i][k - 1]); // Queue station
46             }
47         }
48         double sum = 0.0; // initialize sum
49
50
51         // Compute the sum of V_i * w_i[k] across all stations
52         for (int i = 0; i < M; i++) {
53             sum += V[i] * w[i][k];
54         }
55
56         // Compute throughput for reference job. Remember that the reference
57         // station is the station 0 (delay station)
58         double Xref = k / sum;
59
60         // Compute performance metrics for each station i using MVA
61         // equations seen in class
62         for (int i = 0; i < M; i++) {
63             X[i][k] = V[i] * Xref; // Throughput for station i
64
65             if (ST[i] == 'D') {
66                 // Delay station
67                 n[i][k] = Z * X[i][k];
68                 U[i][k] = n[i][k] / k;
69             } else {
70                 // Computational station
71                 U[i][k] = S[i] * X[i][k]; // Utilization
72                 n[i][k] = U[i][k] * (1 + n[i][k - 1]); // Average queue
73                 // length
74             }
75         }
76
77         // Compute the response time

```

```

74     double Y[M]={0.0,0.0,0.0};
75     for (int i=0; i < M; i++) {
76
77         for (int i = 0; i < M; i++) {
78             Y[i] += V[i] * w[i][k];
79         }
80         if (ST[i] == 'D') {
81             R[i][k] = (k/X[i][k])-Z; //formula for delay station
82         } else {
83             R[i][k] = w[i][N]+S[i];
84         }
85     }
86 }
87 int n_customers = N;
88 // Print results for N = 1 and N = 80;
89 printf("-----\n\n");
90 printf("Simulation with %d customers\n\n", n_customers);
91 for (int i = 0; i < M; i++) {
92     printf("Station %d results:\n", i);
93     printf("Throughput (X[%d])\t\t= %f\n", n_customers, X[i][n_customers
94         ]);
95     printf("Utilization (U[%d])\t\t= %f\n", n_customers, U[i][
96         n_customers]);
97     printf("Mean queue length (n[%d])\t= %f\n", n_customers, n[i][
98         n_customers]);
99     printf("Mean waiting time (w[%d])\t= %f\n", n_customers, w[i][
100         n_customers]);
101     printf("Mean response time (R_0)\t\t= %f\n", (R[i][n_customers
102         ]));
103     printf("\n");
104 }
105 return 0;
106 }

```

This produces the following output:

```
-----
```

Simulation with 10 customers

Station 0 results:

Throughput (X[10])	= 0.002935
Utilization (U[10])	= 0.880562
Mean queue length (n[10])	= 8.805621
Mean waiting time (w[10])	= 3000.000000
Mean response time (R_0)	= 406.914799

Station 1 results:

Throughput (X[10])	= 0.002935
--------------------	------------

Utilization (U[10])	= 0.117408
Mean queue length (n[10])	= 0.131229
Mean waiting time (w[10])	= 44.708658
Mean response time (R_0)	= 84.708658

Station 2 results:

Throughput (X[10])	= 0.000587
Utilization (U[10])	= 0.563560
Mean queue length (n[10])	= 1.063150
Mean waiting time (w[10])	= 1811.030708
Mean response time (R_0)	= 2771.030708

As we can see, the mean waiting time of the station 2 (the long repair station) is really close to the numerical estimation given by the homework request. Again, there is no difference in the eyes of the MVA between this case with the hyper-exponential distribution and the previous case with the exponential distribution.

## 2.3 The simulation

The code of the simulation is untouched with respect to the old version. We only change how the waiting times for the long station are picked inside the `process_event` function, using our new `hyperexponential_random` function. Here is the part of the code that has been changed inside the `process_event` function.

```

1  } else if (current_event.type == 'S') {
2
3  /*
4  Things get trickier: we have two scenarios when processing an S-event.
5  If we do not go to the L station then our machine comes back to the pool and
6  we can schedule its next departure. Otherwise... we need to send it to long
7  repair, where something similar will happen.
8  */
9
10 double last_departure_timestamp = -1.0; // sentinel reset!
11 // first, we decide whether this event is going to the long repair station
12 // or not
13 double coin_flip = (rand() / (double)RAND_MAX);
14 if (coin_flip <= beta) {
15     verbose ? printf("Bad luck, machine %d! You get a long repair! ",
16     current_event.machine)
17     : 0;
18     // go to the long station and schedule the departure event
19     Event current_departure_long;
20     current_departure_long.type = 'L';
21     current_departure_long.machine = current_event.machine;
22     // do the same thing as before
23     for (size_t i = pos; i < event_count; i++) {
24         if (event_list[i].type == 'L') {

```

```

25         last_departure_timestamp = event_list[i].timestamp;
26     }
27 }
28 // we got our sentinel
29 if (last_departure_timestamp == -1.0) {
30     current_departure_long.timestamp =
31     current_event.timestamp +
32     hyperexponential_random(2,alpha,mu); // empty queue
33     verbose
34     ? printf(
35         "But at least there was no one in queue for the long station")
36       : 0;
37 } else {
38     current_departure_long.timestamp =
39     last_departure_timestamp +
40     hyperexponential_random(2,alpha,mu); // someone in the queue
41 }
42 // insert the event
43 add_event(current_departure_long);
44 verbose
45 ? printf("\nAdded departure event %c for machine %d at time %f\n",
46     current_departure_long.type, current_departure_long.machine,
47     current_departure_long.timestamp)
48   : 0;
49
50 /*
51 now we have scheduled the departure from the long station;
52 we are now to calculate the waiting time for this machine
53 to exit the long station
54 */
55 double waiting_time_long = current_departure_long.timestamp -
    current_event.timestamp;
56 double waiting_time_long_squared = pow(waiting_time_long,2);
57 wait_currentcycle_long_station += waiting_time_long;
58 accumulated_wait_long_squared += waiting_time_long_squared;
59 time_events_product_long += waiting_time_long * 1;
60 }

```

After running the simulation, a typical output will look like this:

Stopping conditions reached at the 112663-th iteration

---

```

Simulation complete! :) Execution time: 0.018000 seconds
Total cycles: 10207.
Average waiting time for the long station: 5599.523262
Confidence interval at 10%: (5319.665321,5879.381202).
The error is the 9.995777% of the point estimate.

```

Here the point estimate is tragically higher than the expected value in the previous exercise and than what the MVA suggested. A possible explanation of this fact may lie in the **different variances** of the

two distributions: the exponential distribution has variance

$$\text{Var}[X] = \eta^2 \implies \text{Var}[Y] = 960^2 = 921600 \text{ mins}^2.$$

while for the hyperexponential distribution we have to calculate the second moment  $\mathbb{E}[X^2] = 2 \sum_{i=1}^k \alpha_i \eta_i^2$ :

$$\begin{aligned} \text{Var}[X] &= \mathbb{E}[X^2] - (\mathbb{E}[X])^2 \\ &= 2 \sum_{i=1}^k \alpha_i \eta_i^2 - \left( \sum_{i=1}^k \alpha_i \eta_i \right)^2 \\ &= 2 \cdot \left( 0.95 * 10^2 + 0.05 * 19010^2 \right) - 960 \\ &= 36137240 \text{ mins}^2. \end{aligned}$$

This is more than 40 times the variance of the exponential distribution: most of the times, a small waiting time for the repair of the long station gets chosen and the queue flows quickly; when the other distribution (with a very large parameter) prevails, though, the catastrophic service time makes the queue extremely slow for all the customers in the queue, affecting all their waiting times.