



**STEVENS**  
INSTITUTE *of* TECHNOLOGY  
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# Discrete Event Simulation

*SYS-611: Simulation and Modeling*

Paul T. Grogan, Ph.D.  
Assistant Professor  
School of Systems and Enterprises





# Agenda

1. Queuing Model, Revisited
2. DES Model Constructs
3. DES World Views

Reading: S.M. Ross “The Discrete Event Simulation Approach,” Ch. 7 in *Simulation*, 5<sup>th</sup> Edition, 2013.

Optional: A.M. Law, “Basic Simulation Modeling,” Ch. 1 in *Simulation Modeling and Analysis*, 5<sup>th</sup> Edition, 2014.

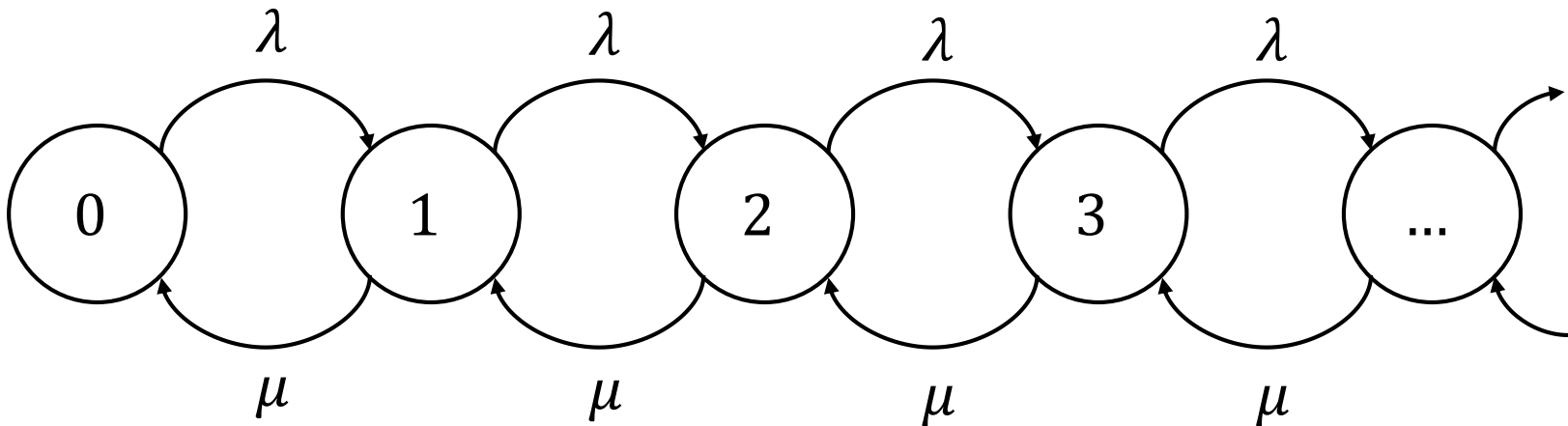


# Queuing Model, Revisited



# Queuing Model Review

- Continuous-time Markov Process
- State  $q$  measures number customers in system
- Inter-arrival periods ( $X \sim \text{exponential}(\lambda)$ )
- Service times ( $Y \sim \text{exponential}(\mu)$ )



# Results of Queuing Theory

- Steady-state assumption helps to solve for the stationary stochastic distribution  $P_i$  in terms of  $P_0$
- Geometric series converges to analytic result

$$\begin{aligned}\bar{L}_q &= \frac{\lambda^2}{\mu(\mu - \lambda)}, & \bar{L} &= \frac{\lambda}{\mu - \lambda} \\ \bar{W}_q &= \frac{\lambda}{\mu(\mu - \lambda)}, & \bar{W} &= \frac{1}{\mu - \lambda}\end{aligned}$$

# M/M/1 Model Simulation



If  $q(t) = 0$ :

$$q(t + x) = 1$$

$$x = -\frac{\ln(1 - r_x)}{\lambda}, \lambda = 2/3$$

If  $q(t) > 0$ :

$$q(t + \Delta t) = \begin{cases} q(t) + 1 & \text{if } x < y \\ q(t) - 1 & \text{if } y < x \end{cases}$$

$$y = -\frac{\ln(1 - r_y)}{\mu}, \mu = 4/3$$

$$\Delta t = \min(x, y)$$

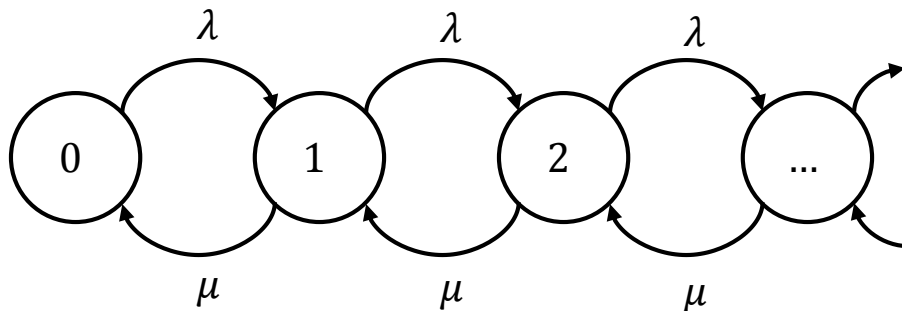
State transition function:

If  $q(t) = 0$  or  $x < y$ :

$$q(t + x) = q(t) + 1$$

If  $q(t) > 0$  and  $y < x$ :

$$q(t + y) = q(t) - 1$$





# M/M/1 Model Limitations

- Simplified for mathematical convenience:
- Exponentially-distributed arrivals, service times
  - Independent with long-term average rates
  - Memoryless: can resample  $x, y$  for every event
- Single queue, single server
  - Simplifies state representation
- No human behaviors (reneging, balking, etc.)
  - Simplifies state transitions



# Customer-based Simulation

Allow different arrival and service duration models by indexing states with customer  $i$  instead of event  $i$

- $t_{enter}^i$ : time customer  $i$  enters the system
- $L_q^i$ : length of the queue when customer  $i$  enters
- $t_{serv}^i$ : time customer  $i$  service starts
- $W_q^i$ : waiting time in the queue for customer  $i$
- $t_{exit}^i$ : time customer  $i$  exists the system
- $W^i$ : total waiting time for customer  $i$





# Customer-based Simulation

$x$ : Inter-arrival Period  
 $y$ : Service Time

$t_{enter}$ : Entry Time  
 $t_{serv}$ : Time Served  
 $t_{exit}$ : Exit Time

$L_q$ : Queue Length  
 $W_q$ : Queue Wait Time  
 $W$ : Total Wait Time

$i$	$x$	$t_{enter}$	$L_q$	$t_{serv}$	$W_q$	$y$	$t_{exit}$	$W$
1	0.43					0.90		
2	4.49					1.66		
3	0.95					0.02		
4	0.03					0.46		
5	0.28					0.51		



# Customer-based Simulation

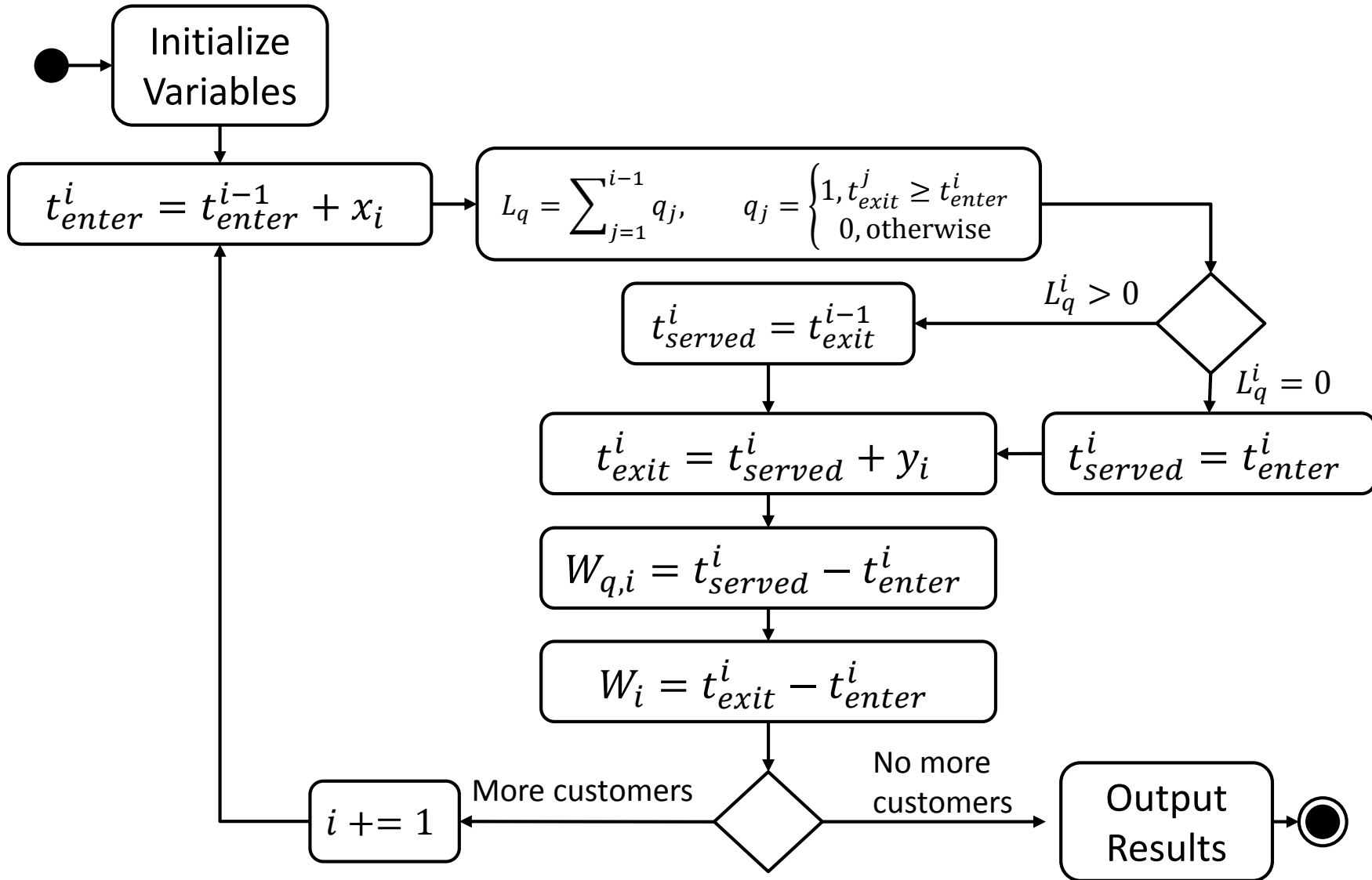
$x$ : Inter-arrival Period  
 $y$ : Service Time

$t_{enter}$ : Entry Time  
 $t_{serv}$ : Time Served  
 $t_{exit}$ : Exit Time

$L_q$ : Queue Length  
 $W_q$ : Queue Wait Time  
 $W$ : Total Wait Time

$i$	$x$	$t_{enter}$	$L_q$	$t_{serv}$	$W_q$	$y$	$t_{exit}$	$W$
1	<b>0.43</b>	0.00+0.43= 0.43	0	0.43	0.43-0.43= 0	<b>0.90</b>	0.43+0.90= 1.33	1.33-0.43= 0.90
2	<b>4.49</b>	0.43+4.49= 4.92	0	4.92	4.92-4.92= 0	<b>1.66</b>	4.92+1.66= 6.58	6.58-4.92= 1.66
3	<b>0.95</b>	4.92+0.95= 5.87	1	6.58	6.58-5.87= 0.71	<b>0.02</b>	6.58+0.02= 6.60	6.60-5.87= 0.73
4	<b>0.03</b>	5.87+0.03= 5.90	2	6.60	6.60-5.90= 0.70	<b>0.46</b>	6.60+0.46= 7.06	7.06-5.90= 1.16
5	<b>0.28</b>	5.90+0.28= 6.18	3	7.06	7.06-6.18= 0.88	<b>0.51</b>	7.06+0.51= 7.57	7.57-6.18= 1.39

# Customer-based Sim Behavior





# Customer-based Sim (Excel)

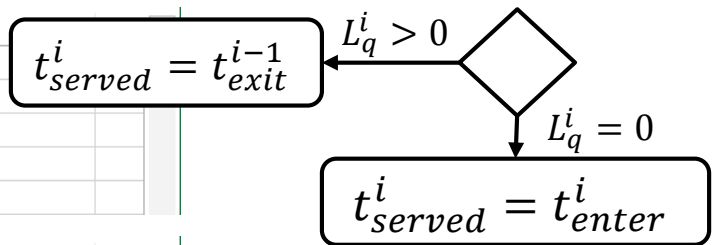
	A	B	C	D	E	F	G	H	I	J
1	Customer	x	t_enter	L_q	t_served	y	t_exit	W_q	W	
2	1	0.44	0.44	0	0.44	2.21	2.64	2.21	2.21	
3	2	4.25	4.69	0	4.69	0.13	4.81	0.13	0.13	
4	3	0.74	=B4+C3	0	5.43	0.57	6.00	0.57	0.57	

$$t_{enter}^i = t_{enter}^{i-1} + x_i$$

	A	B	C	D	E	F	G	H	I	J
1	Customer	x	t_enter	L_q	t_served	y	t_exit	W_q	W	
2	1	0.44	0.44	0	0.44	2.21	2.64	2.21	2.21	
3	2	4.25	4.69	0	4.69	0.13	4.81	0.13	0.13	
4	3	0.74	5.43	=COUNTIF(\$G\$2:G3,">="&C4)			6.00	0.57	0.57	

$$L_q = \sum_{j=1}^{i-1} q_j, \quad q_j = \begin{cases} 1, & t_{exit}^j \geq t_{enter}^i \\ 0, & \text{otherwise} \end{cases}$$

	A	B	C	D	E	F	G	H	I	J
1	Customer	x	t_enter	L_q	t_served	y	t_exit	W_q	W	
2	1	0.39	0.39	0	0.39	0.71	1.11	0.71	0.71	
3	2	0.24	0.63	1	1.11	0.24	1.35	0.24	0.71	
4	3	3.05	3.68	0	=IF(D4=0,C4,G3)		3.73	0.05	0.05	
5	4	1.91	5.59	0	5.59	0.44	6.03	0.44	0.44	



$$t_{exit}^i = t_{served}^i + y_i$$

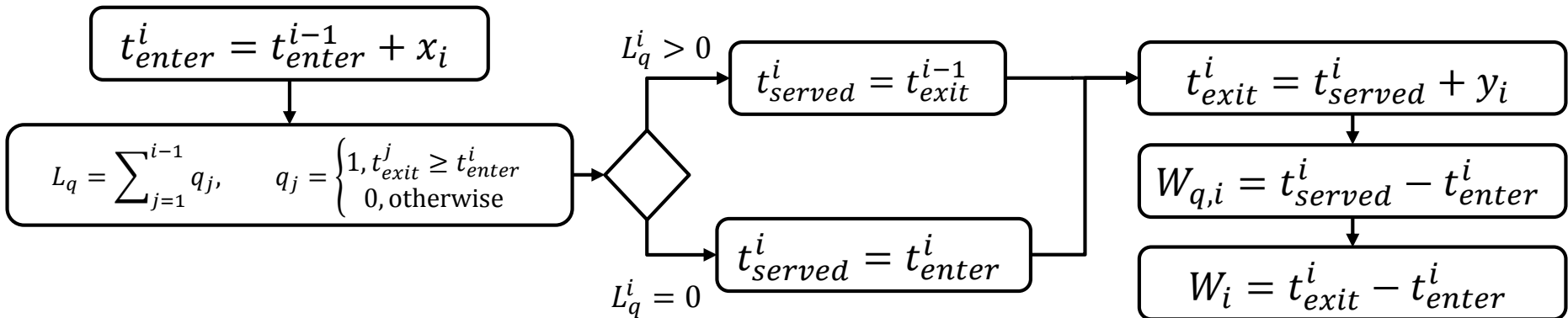
	A	B	C	D	E	F	G	H	I	J
1	Customer	x	t_enter	L_q	t_served	y	t_exit	W_q	W	
2	1	0.92	0.92	0	0.92	0.64	1.55	0.64	0.64	
3	2	0.39	1.31	1	1.55	0.26	1.82	0.26	0.51	
4	3	2.13	3.44	0	3.44	1.69	=F4+E4	1.69	1.69	

$$W_{q,i} = t_{exit}^i - t_{served}^i$$

	A	B	C	D	E	F	G	H	I	J
1	Customer	x	t_enter	L_q	t_served	y	t_exit	W_q	W	
2	1	1.62	1.62	0	1.62	0.31	1.93	0.31	0.31	
3	2	1.95	3.56	0	3.56	0.26	3.83	0.26	0.26	
4	3	3.00	6.57	0	6.57	2.34	8.90	=G4-E4	2.34	

# Customer-based Sim (Python)

```
for i in range(num_customers):
    t_enter[i] = t_enter[i-1] + x[i] if i > 0 else x[i]
    q_length[i] = np.sum(t_exit[0:i] > t_enter[i]) if i > 0 else 0
    t_served[i] = t_exit[i-1] if q_length[i] > 0 else t_enter[i]
    t_exit[i] = t_served[i] + y[i]
    q_wait[i] = t_served[i] - t_enter[i]
    total_wait[i] = t_exit[i] - t_enter[i]
```





# Customer-based Simulation

$$\lambda = 2/3 \quad \mu = 4/3$$

1000-customer Sim.:

- $\bar{W} = 1.49$  min.
- $\bar{W}_q = 0.74$  min.
- $\bar{L}_q^* = 1.05$  cust.
- $\bar{L}^* = \bar{L}_q^* + 1 = 2.05$  cust.

Queuing Theory:

- $\bar{W} = \frac{1}{\mu - \lambda} = 1.50$  min.
- $\bar{W}_q = \frac{\lambda}{\mu(\mu - \lambda)} = 0.75$  min.
- $\bar{L} = \frac{\lambda}{\mu - \lambda} = 1.00$  cust.
- $\bar{L}_q = \frac{\lambda^2}{\mu(\mu - \lambda)} = 0.50$  cust.

- Length observations *only* recorded at arrivals
- Biased sample, more customers arrive in long lines (by definition)
- Issue of “**random incidence**”: need to take independent samples

# Customer-based Simulation



## Strengths

- Can use arbitrary process generators for all arrival times and service times (if state independent)
- Straight-forward, intuitive state updating

## Limitations

- Need to maintain history of all customers
- Difficult to calculate time-average results
- Difficult to extend to new problems:
  - Balking, reneging



# DES Model Constructs







# Discrete Event Simulation

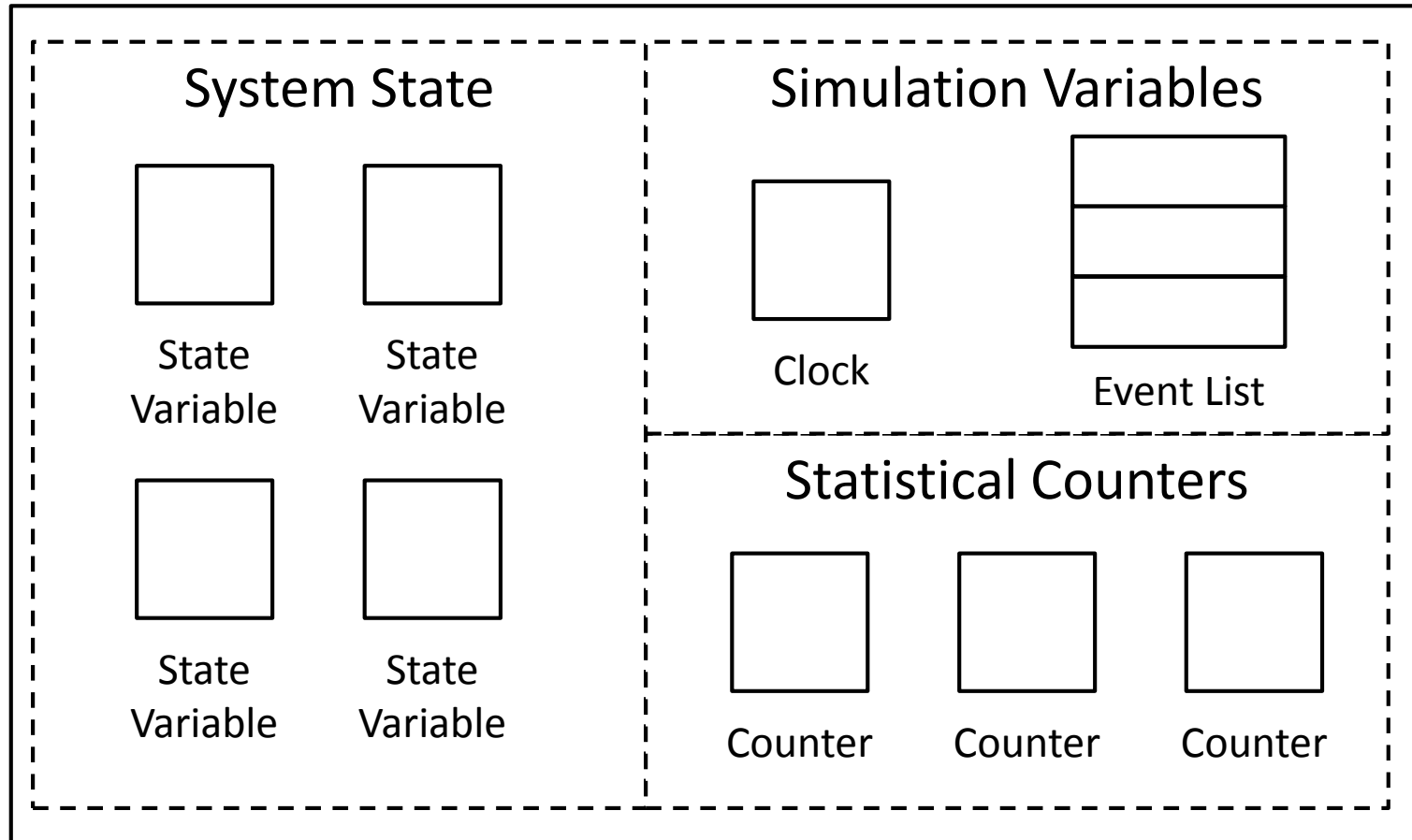
- **Discrete event simulation (DES)** is a modeling approach which represents state transitions at particular instants in time (events)
  - Efficiently models systems with occasional state transitions (e.g. logistics, operations)
  - Example: queuing model with general (non-Markov) arrivals and services
- Discrete time simulation is a special type of DES with evenly-distributed events (clock ticks)



# DES Model Constructs

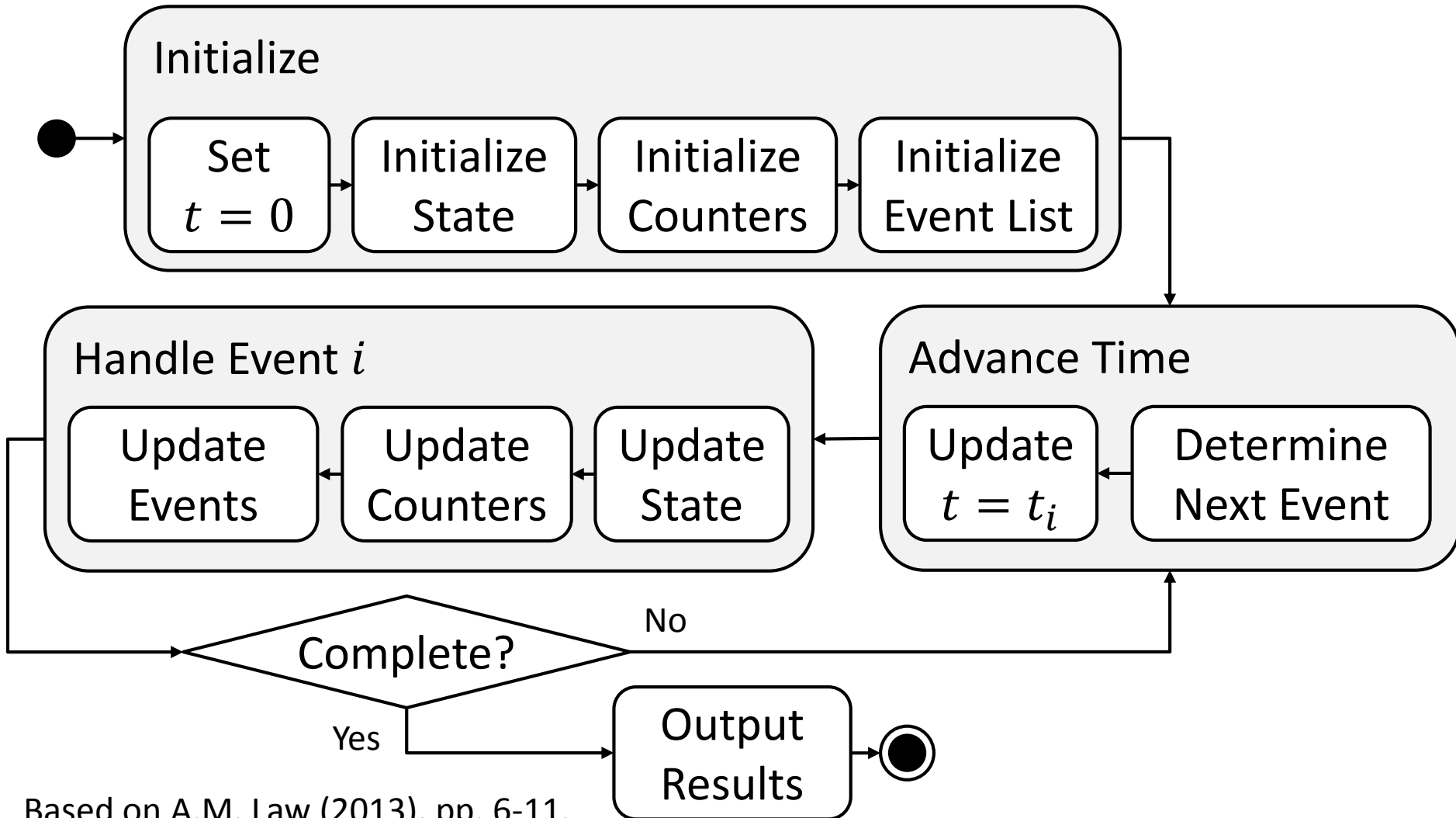
- **Time variable:** keeps track of the current simulation time
- **Event list/stack:** List of future events with associated execution times
- **System state variables:** Stores variables which persist across time
- **Counter variables:** Derived state variables to record useful observations

# DES Model Structure



Based on A.M. Law (2013), pp. 6-11.

# DES Model Behavior



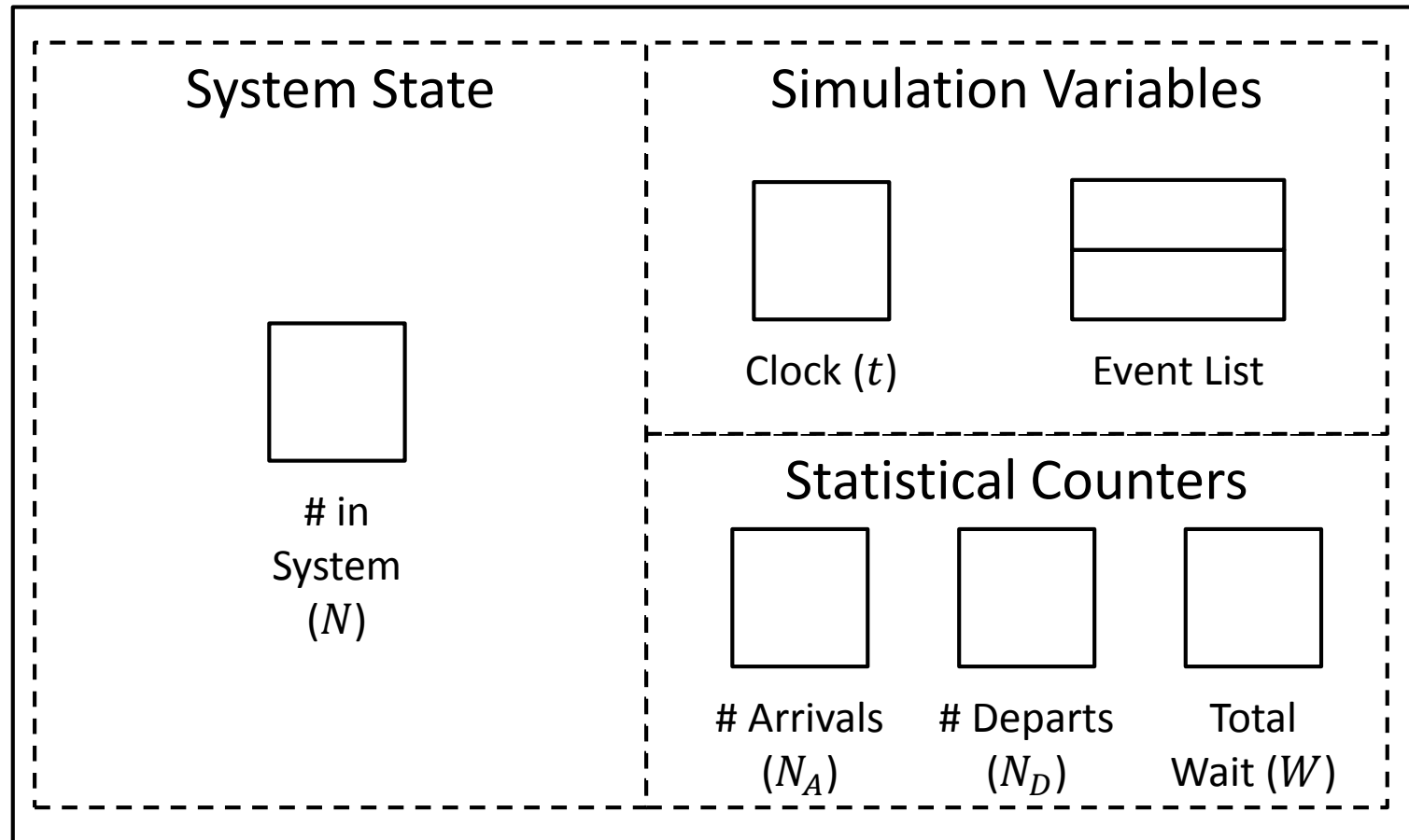
Based on A.M. Law (2013), pp. 6-11.

# Event-based Queuing Model



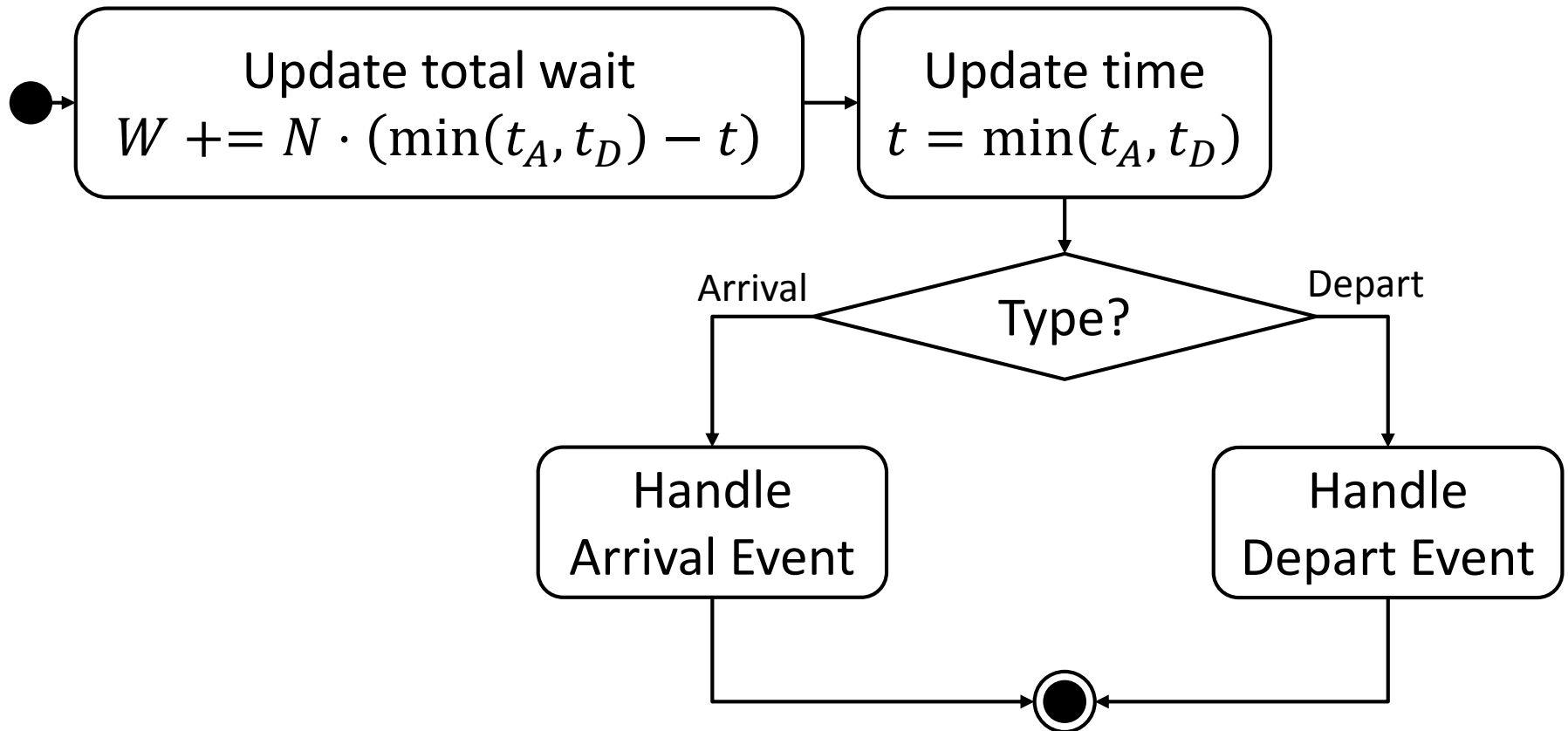
Inter-arrival times: 0.4, 1.2, 0.5, 1.7

Service times: 2.0, 0.7, 0.2, 1.1

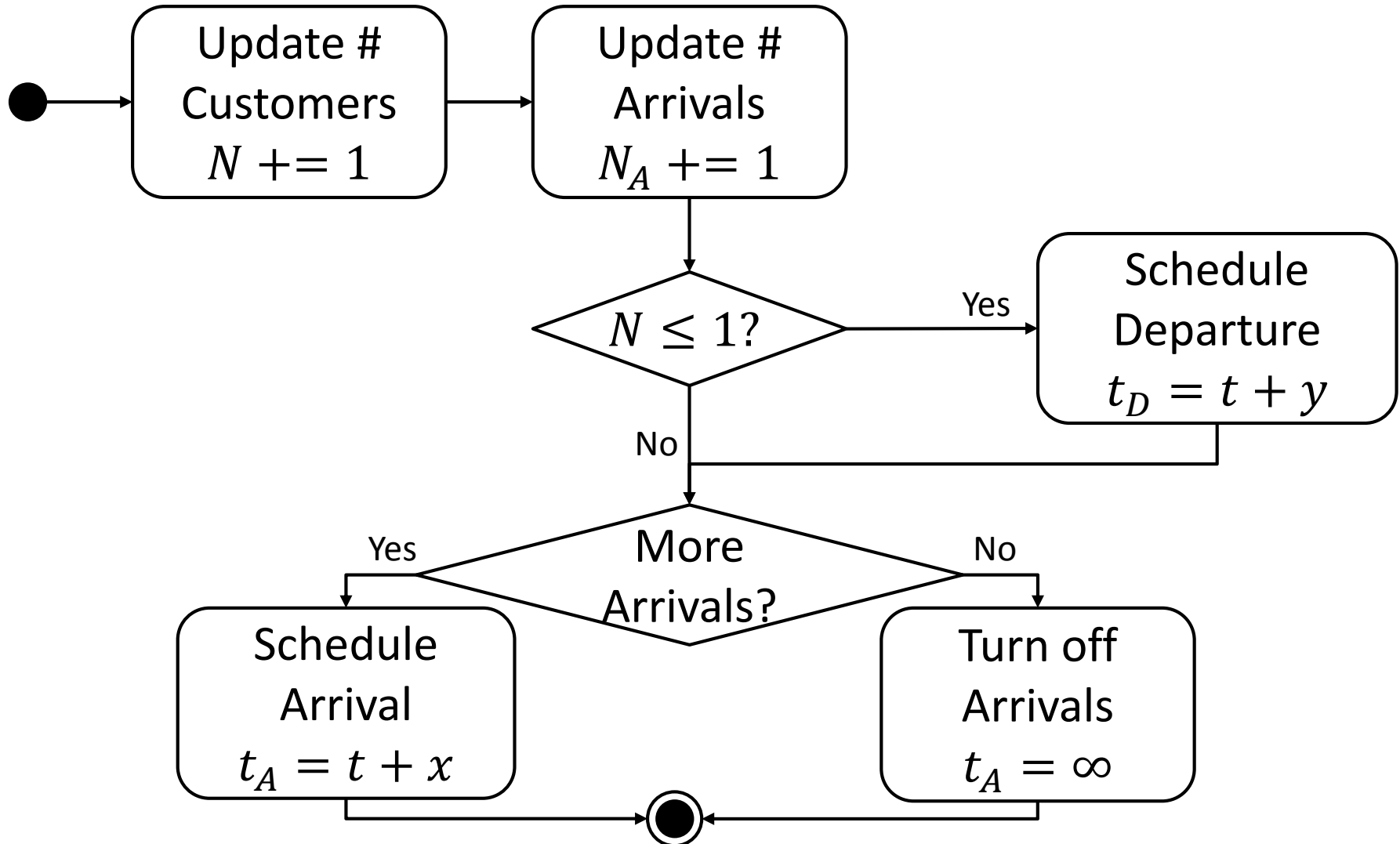


Based on A.M. Law (2013), pp. 12-27.

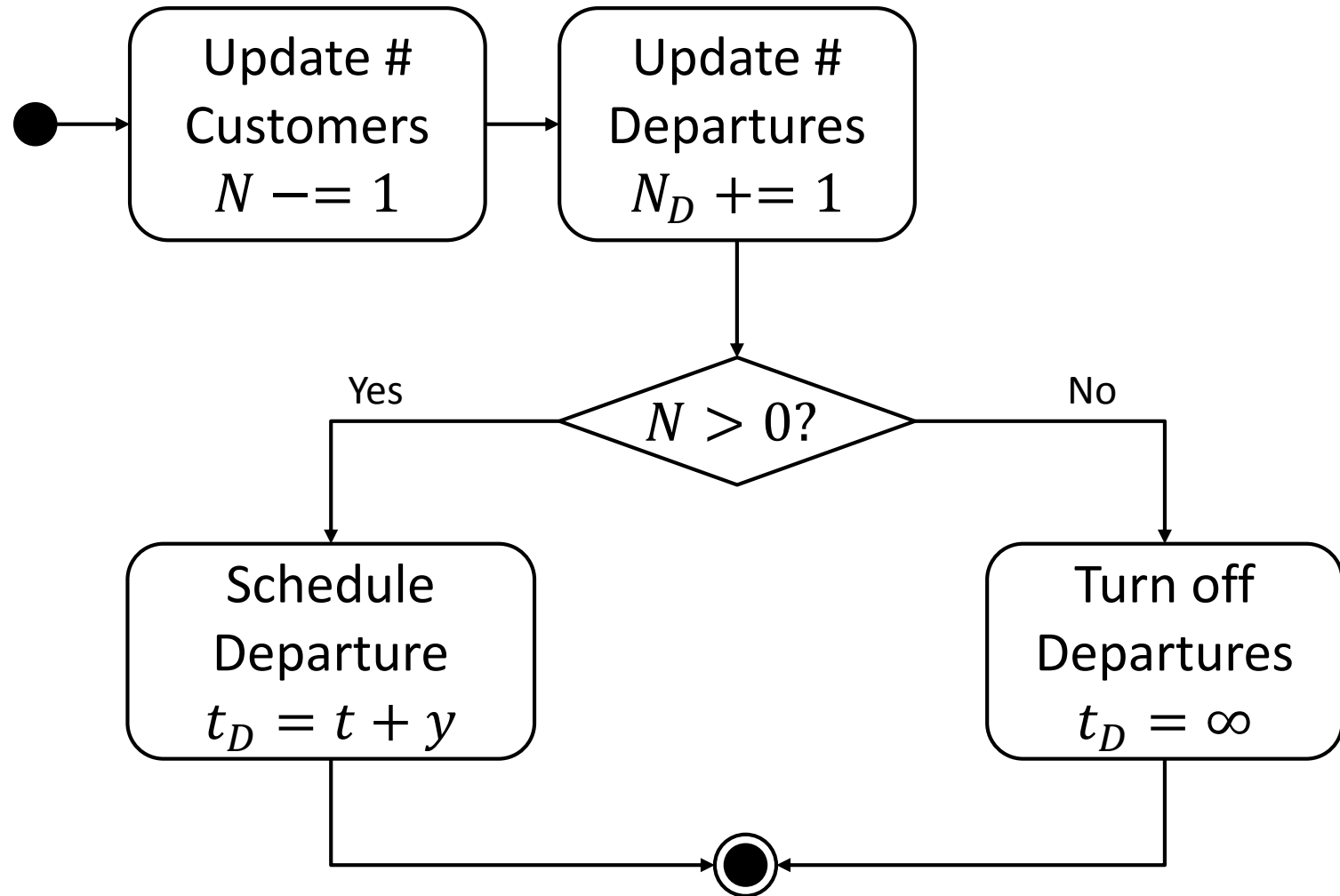
# Advance Time / Handle Event



# Handle Arrival Event

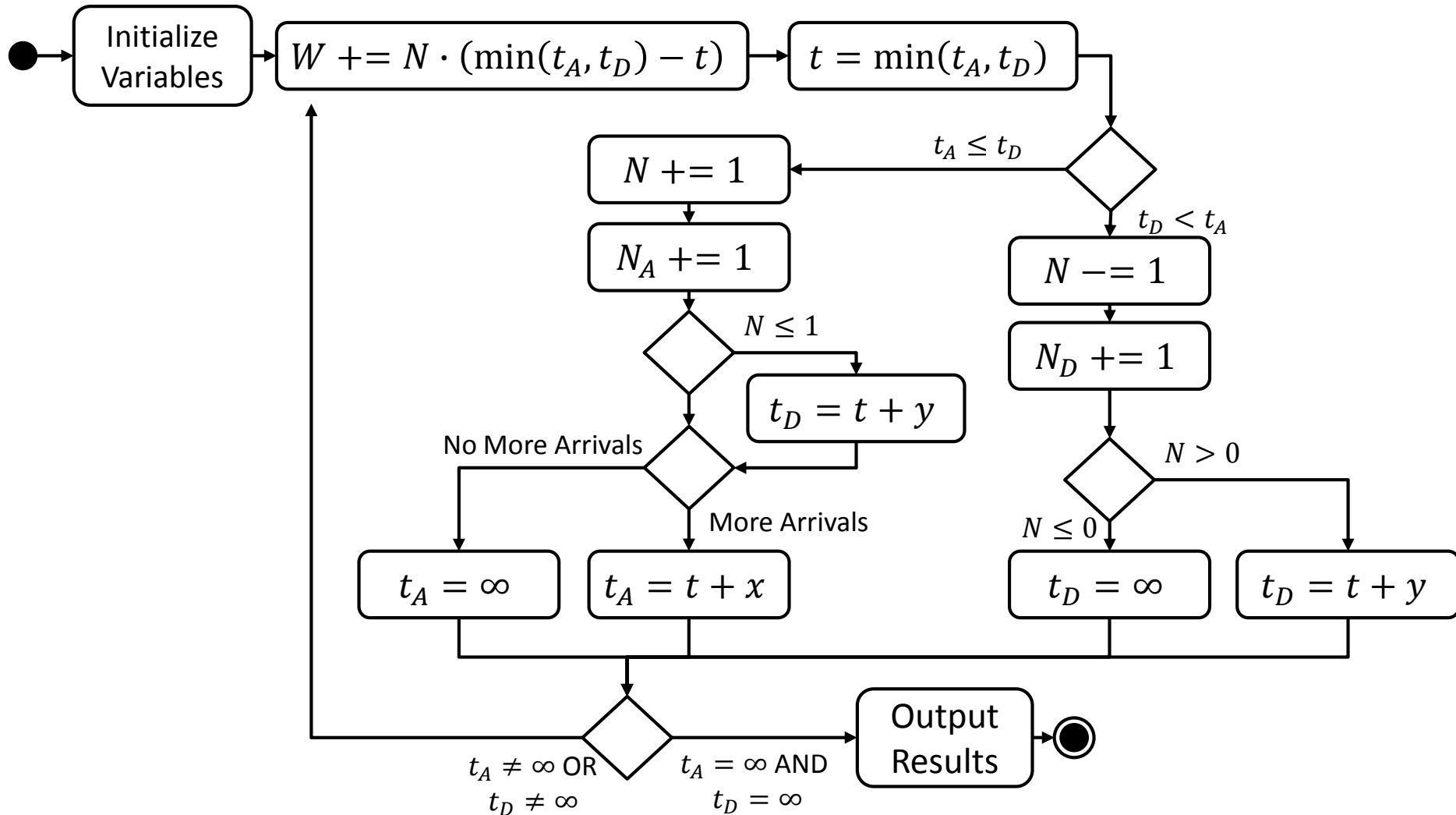


# Handle Departure Event





# Complete Activity Diagram

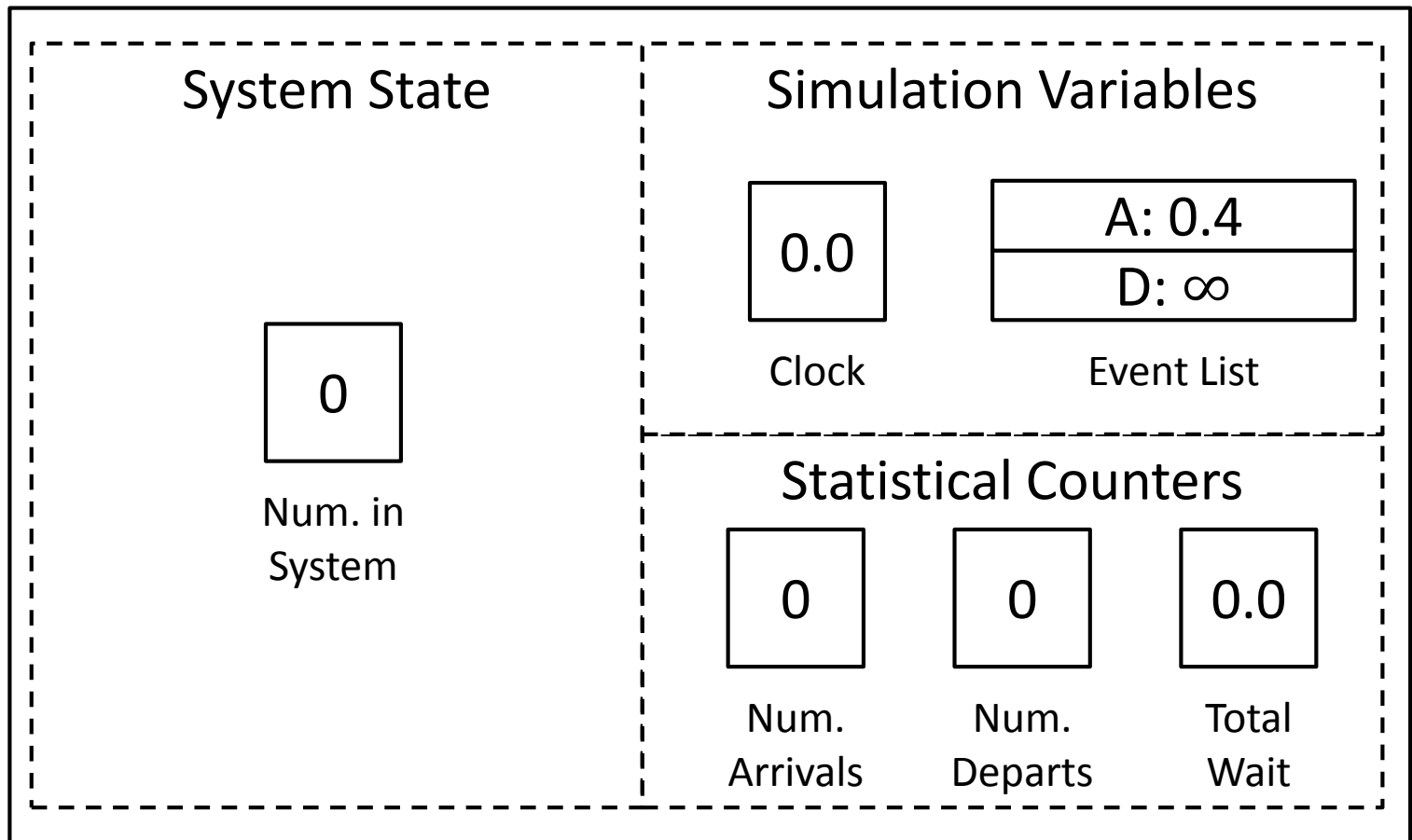




# Initialize Simulation

Inter-arrival times: 0.4, 1.2, 0.5, 1.7

Service times: 2.0, 0.7, 0.2, 1.1



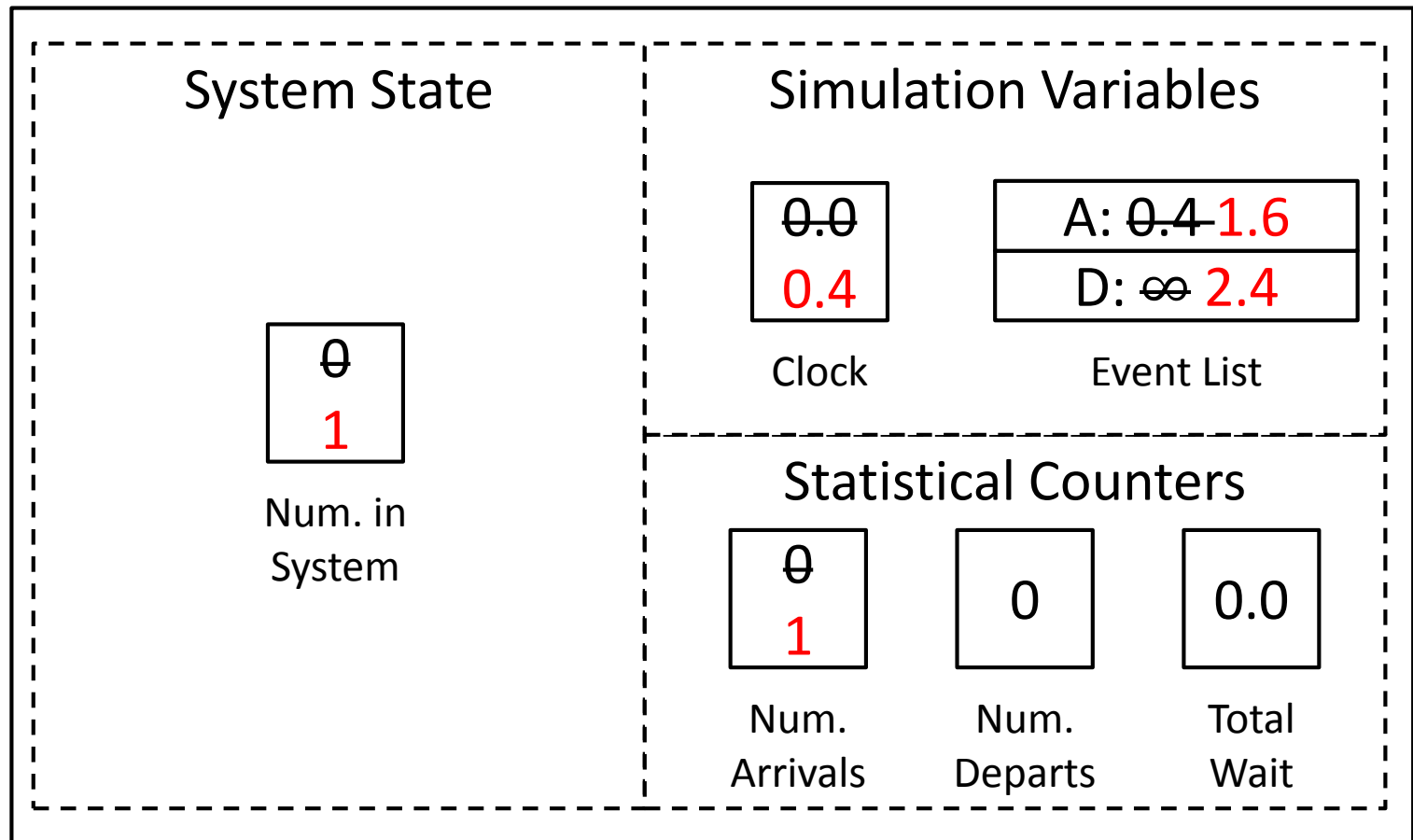
Based on A.M. Law (2013), pp. 12-27.



# Arrival Event @ $t = 0.4$

Inter-arrival times: ~~0.4~~, 1.2, 0.5, 1.7

Service times: 2.0, 0.7, 0.2, 1.1



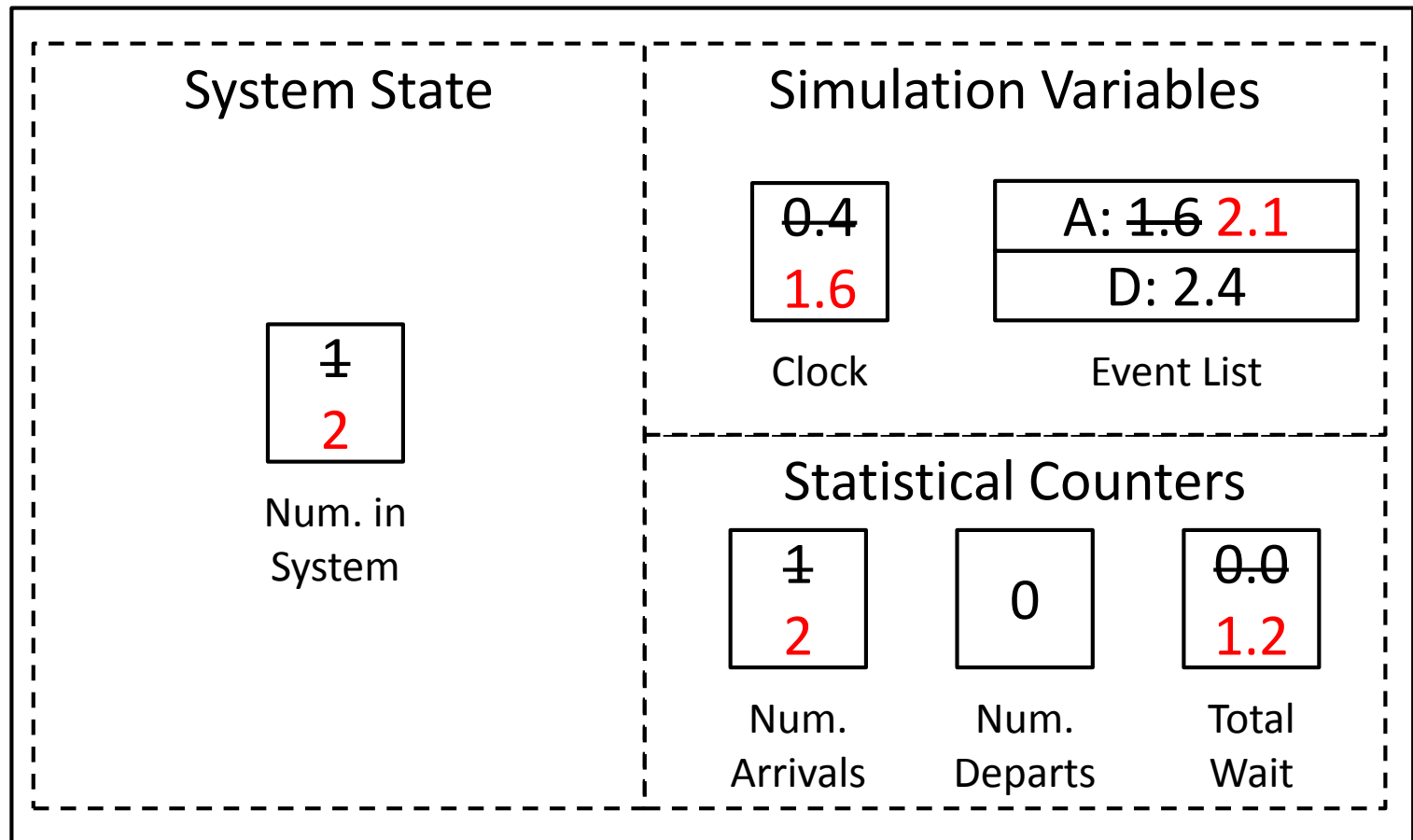
Based on A.M. Law (2013), pp. 12-27.



# Arrival Event @ $t = 1.6$

Inter-arrival times: ~~0.4~~, ~~1.2~~, **0.5**, 1.7

Service times: ~~2.0~~, 0.7, 0.2, 1.1



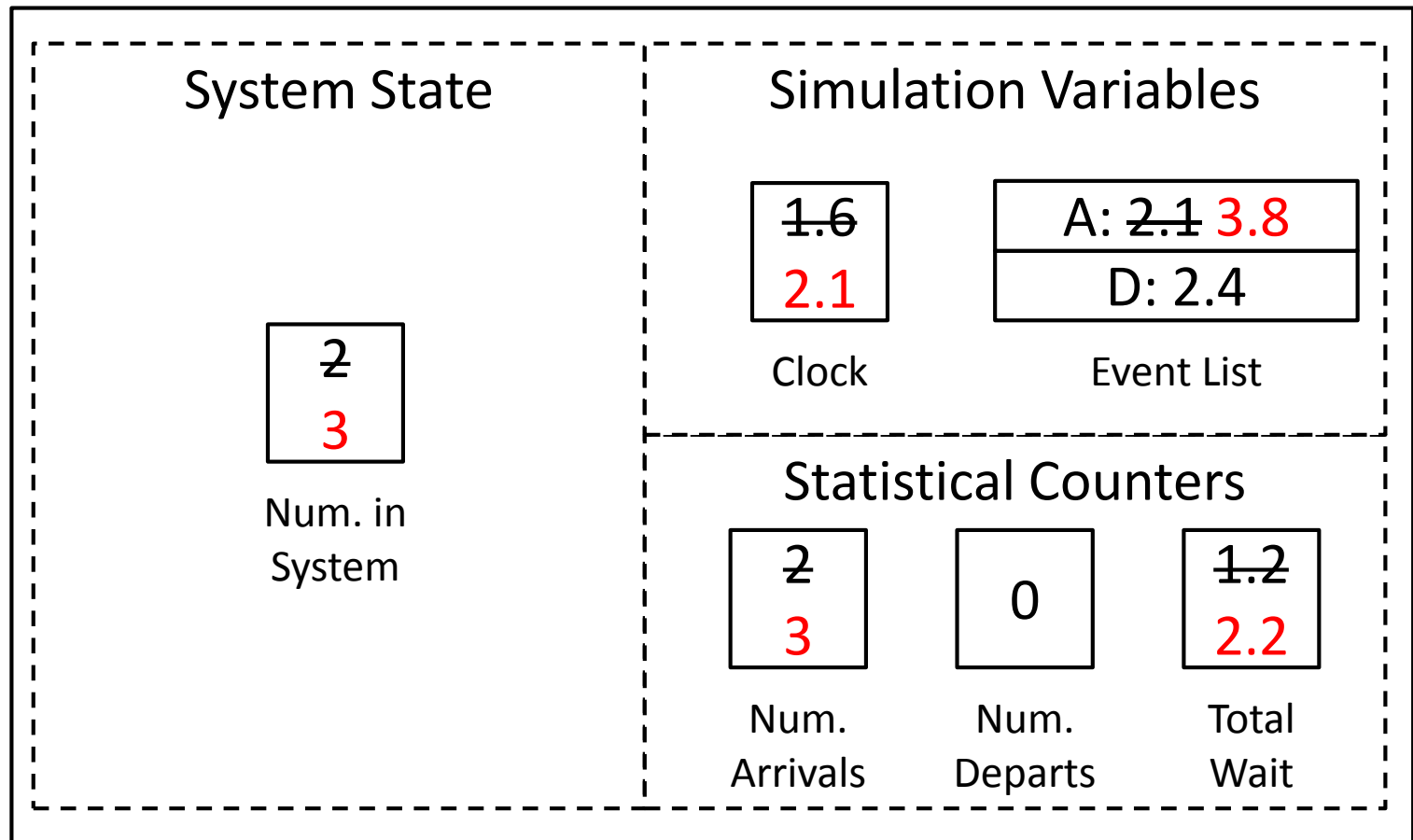
Based on A.M. Law (2013), pp. 12-27.



# Arrival Event @ $t = 2.1$

Inter-arrival times: ~~0.4~~, ~~1.2~~, ~~0.5~~, **1.7**

Service times: ~~2.0~~, 0.7, 0.2, 1.1



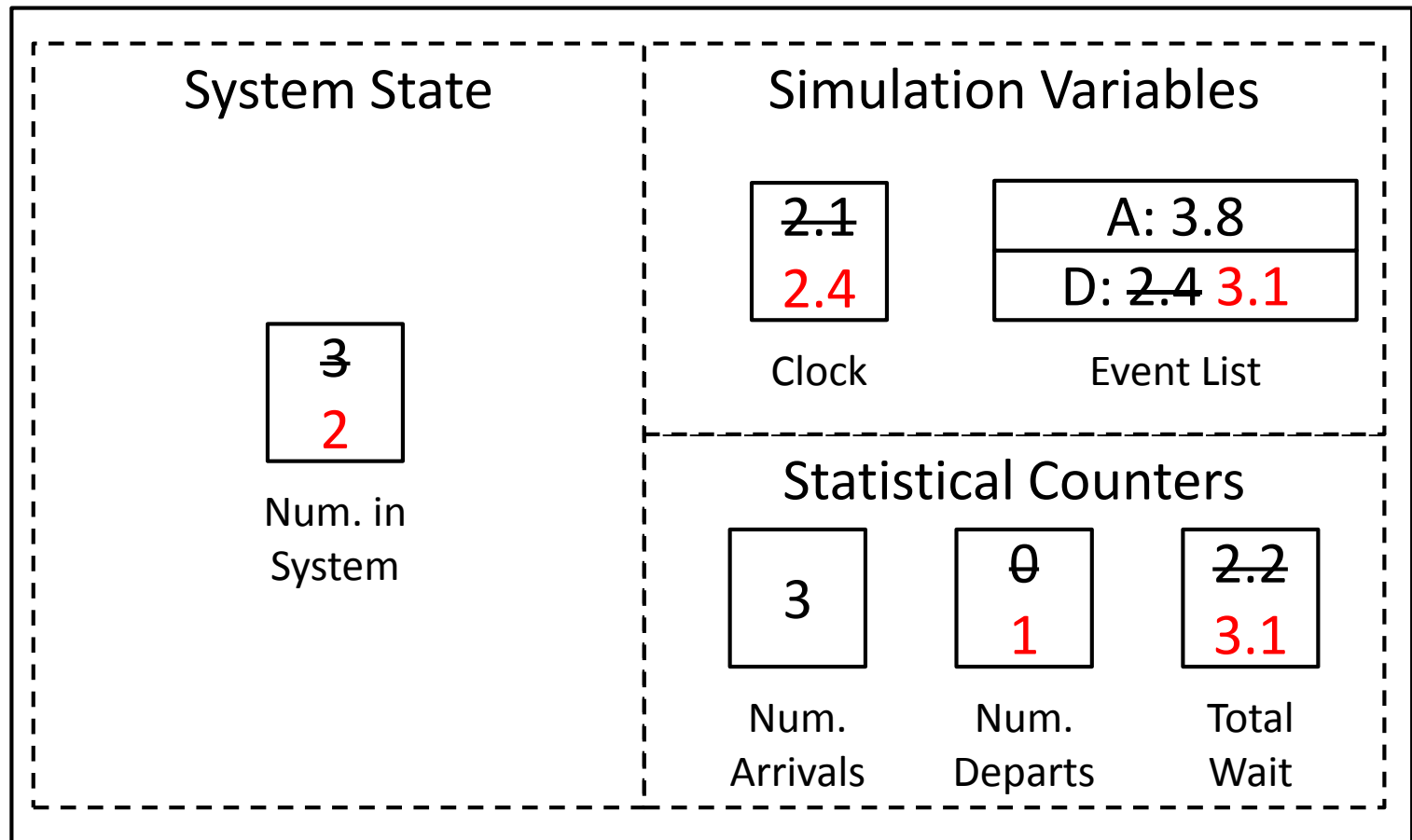
Based on A.M. Law (2013), pp. 12-27.

# Departure Event @ $t = 2.4$



Inter-arrival times: ~~0.4~~, ~~1.2~~, ~~0.5~~, ~~1.7~~

Service times: ~~2.0~~, **0.7**, 0.2, 1.1



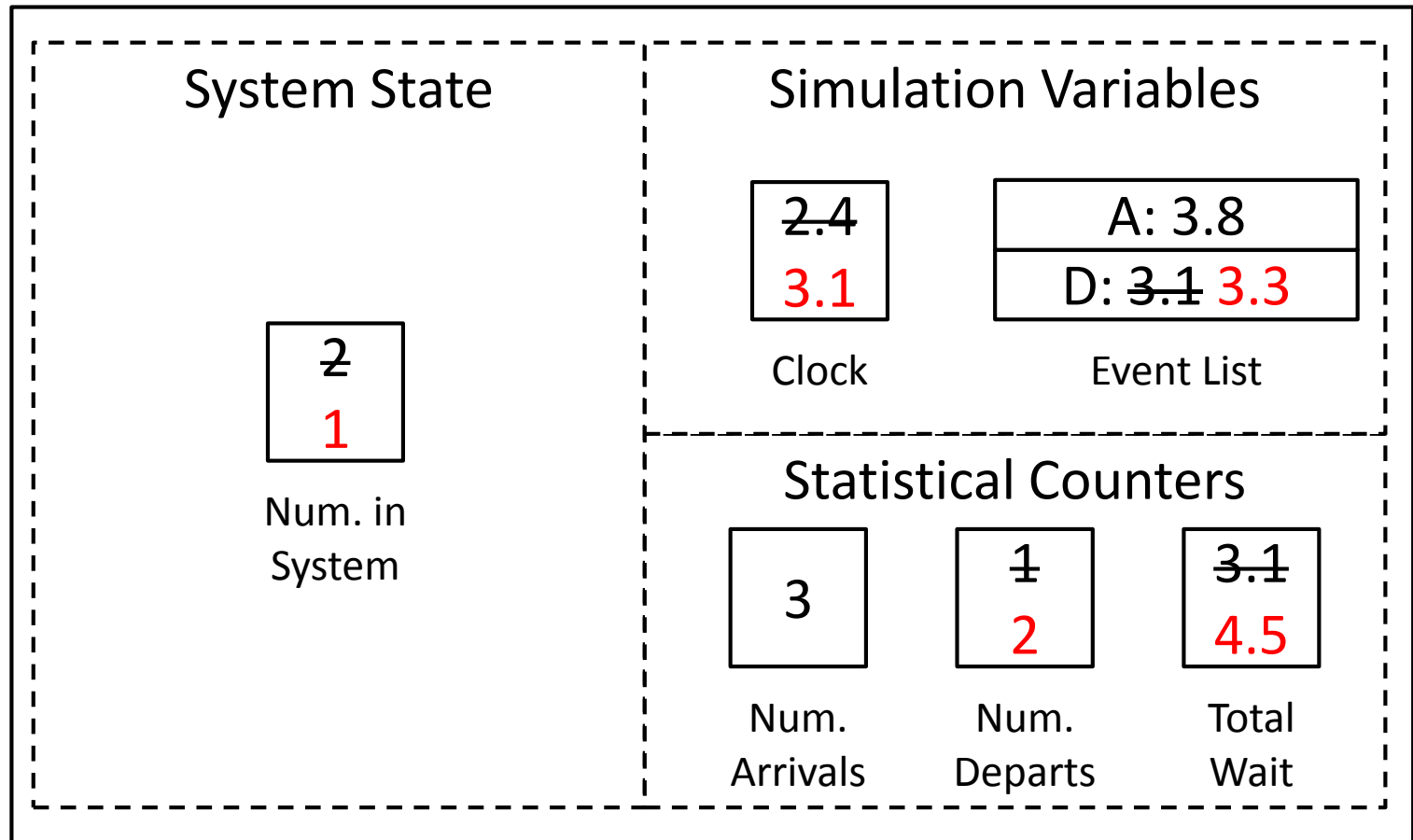
Based on A.M. Law (2013), pp. 12-27.

# Departure Event @ $t = 3.1$



Inter-arrival times: ~~0.4~~, ~~1.2~~, ~~0.5~~, ~~1.7~~

Service times: ~~2.0~~, ~~0.7~~, **0.2**, 1.1



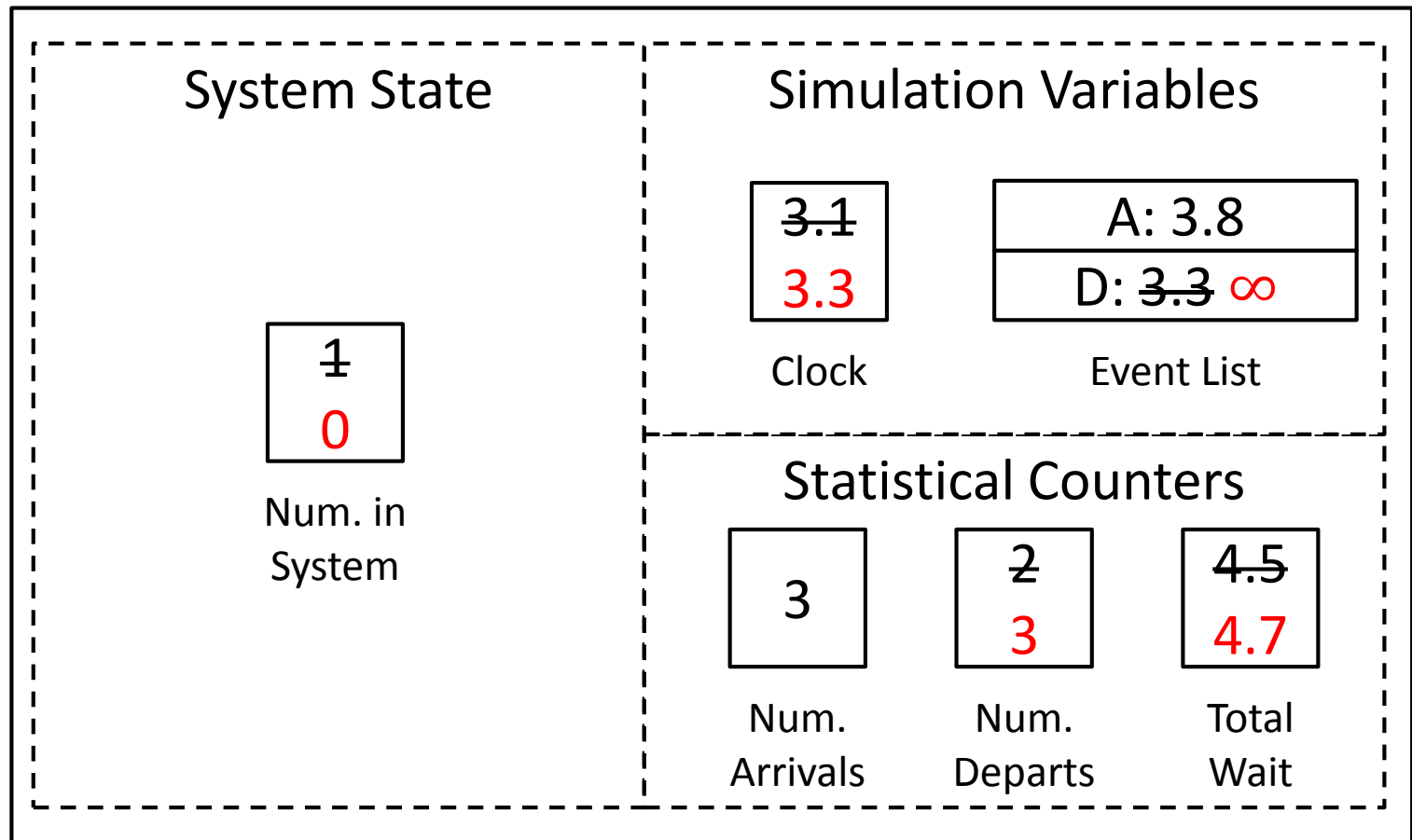
Based on A.M. Law (2013), pp. 12-27.

# Departure Event @ $t = 3.3$



Inter-arrival times: ~~0.4~~, ~~1.2~~, ~~0.5~~, ~~1.7~~

Service times: ~~2.0~~, ~~0.7~~, ~~0.2~~, **1.1**



Based on A.M. Law (2013), pp. 12-27.

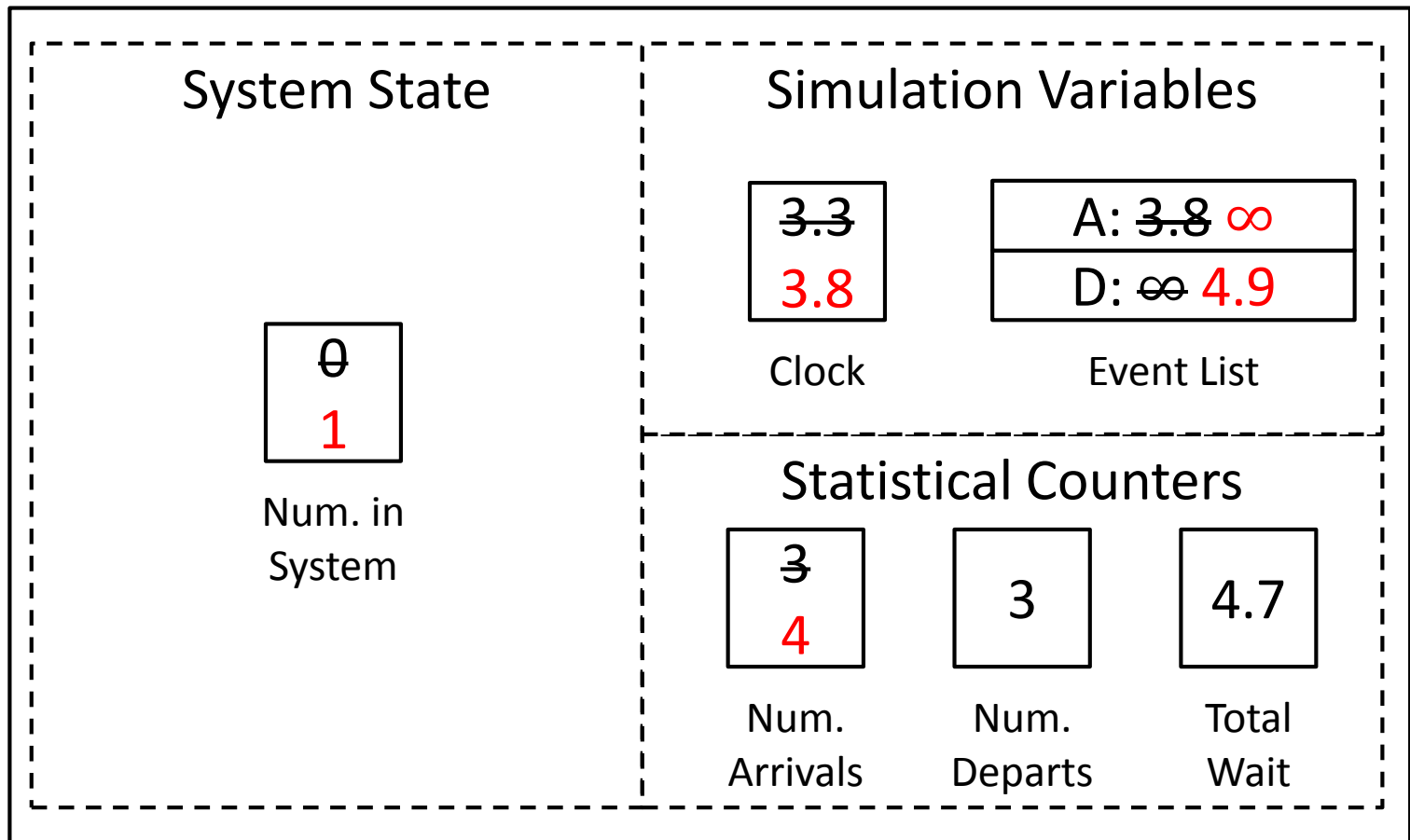




# Arrival Event @ $t = 3.8$

Inter-arrival times: ~~0.4~~, ~~1.2~~, ~~0.5~~, ~~1.7~~

Service times: ~~2.0~~, ~~0.7~~, ~~0.2~~, ~~1.1~~



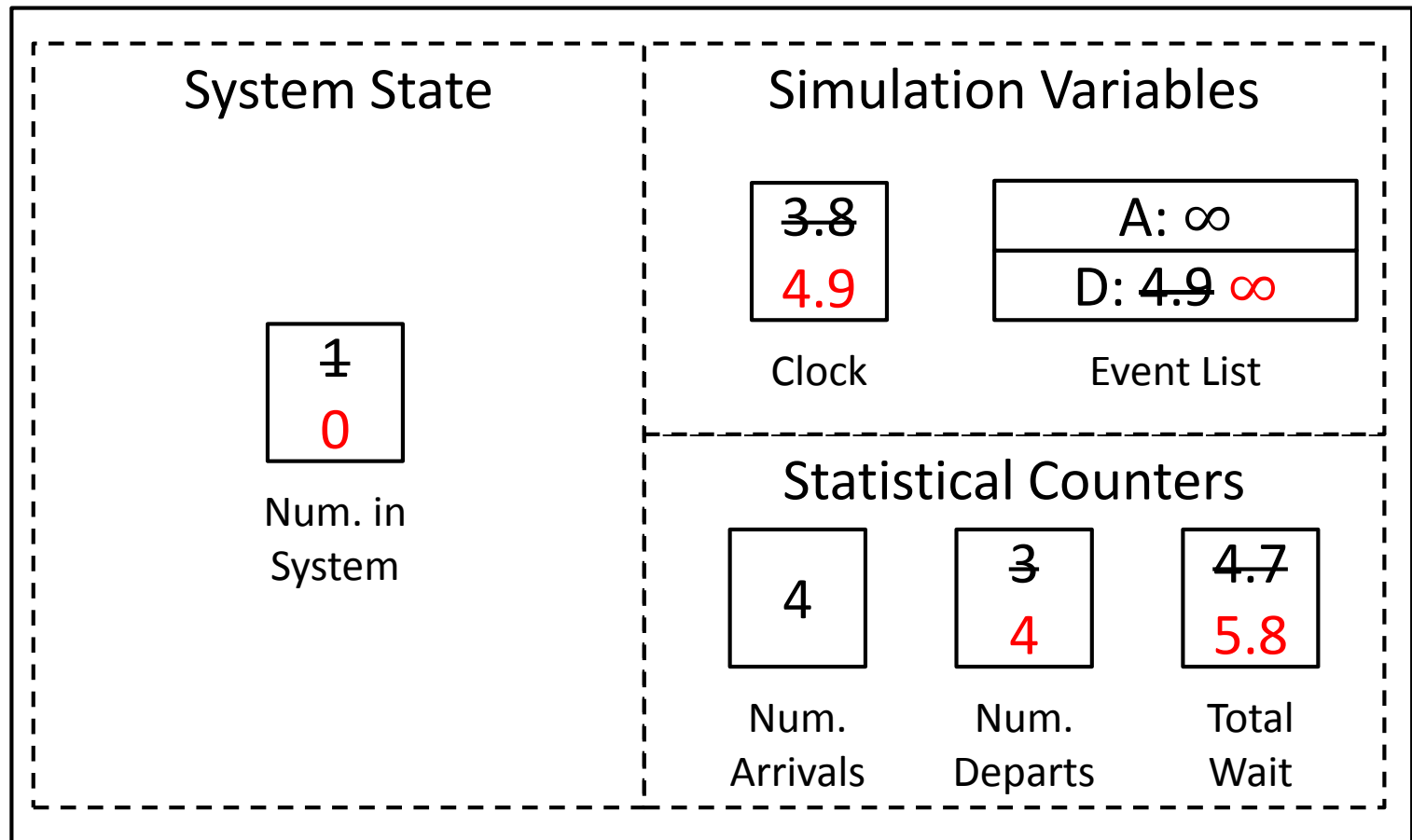
Based on A.M. Law (2013), pp. 12-27.

# Departure Event @ $t = 4.9$



Inter-arrival times: ~~0.4~~, ~~1.2~~, ~~0.5~~, ~~1.7~~

Service times: ~~2.0~~, ~~0.7~~, ~~0.2~~, ~~1.1~~



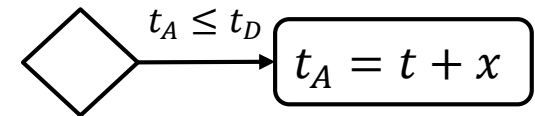
Based on A.M. Law (2013), pp. 12-27.

# Event-based Sim (Excel)

	A	B	C	D	E	F	G	H
1	Event	t	t_A	t_D	N	N_A	N_D	W
2	0	0	0.33	9999.00	0	0	0	0.00
3	1	=MIN(C2:D2)		0.80	1	1	0	0.00

$$t_e = \min(t_A, t_D)$$

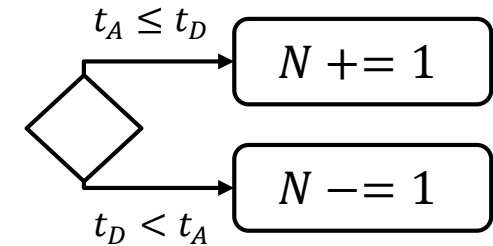
	A	B	C	D	E	F	G	H
1	Event	t	t_A	t_D	N	N_A	N_D	W
2	0	0	0.77	9999.00	0	0	0	0.00
3	1	0.77	=IF(C2<=D2,B3-1.5*LN(1-RAND()),C2)				0	0.00



	A	B	C	D	E	F	G	H	I	J	K
1	Event	t	t_A	t_D	N	N_A	N_D	W		W_bar	
2	0	0	0.04	9999.00	0	0	0	0.00		1.84	
3	1	0.04	0.88	=IF(OR(AND(C2<=D2,E2+1<=1),AND(D2<C2,E2-1>0)),B3-0.75*LN(1-RAND()),IF(AND(D2<C2,E2-1<=0),9999,D2))							
4	2	0.88	7.96								

Complicated!!

	A	B	C	D	E	F	G	H
1	Event	t	t_A	t_D	N	N_A	N_D	W
2	0	0	2.88	9999.00	0	0	0	0.00
3	1	2.88	3.00	4.63	=IF(C2<=D2,E2+1,E2-1)			0.00
4	2	3.00	4.62	4.63	2	2	0	0.12



	A	B	C	D	E	F	G	H	I
1	Event	t	t_A	t_D	N	N_A	N_D	W	
2	0	0	2.56	9999.00	0	0	0	0.00	
3	1	2.56	4.36	3.48	1	1	0	=H2+E2*(B3-B2)	
4	2	3.48	4.36	9999.00	0	1	1	0.93	

$$W += N \cdot (\min(t_A, t_D) - t)$$

# Event-based Sim (Python)



```
while t_A < np.inf or t_D < np.inf:
```

```
    W += N*(min(t_A, t_D) - t)
```

```
    t = min(t_A, t_D)
```

```
    if t_A <= t_D:
```

```
        N += 1
```

```
        N_A += 1
```

```
        if N <= 1:
```

```
            t_D = t + generate_y()
```

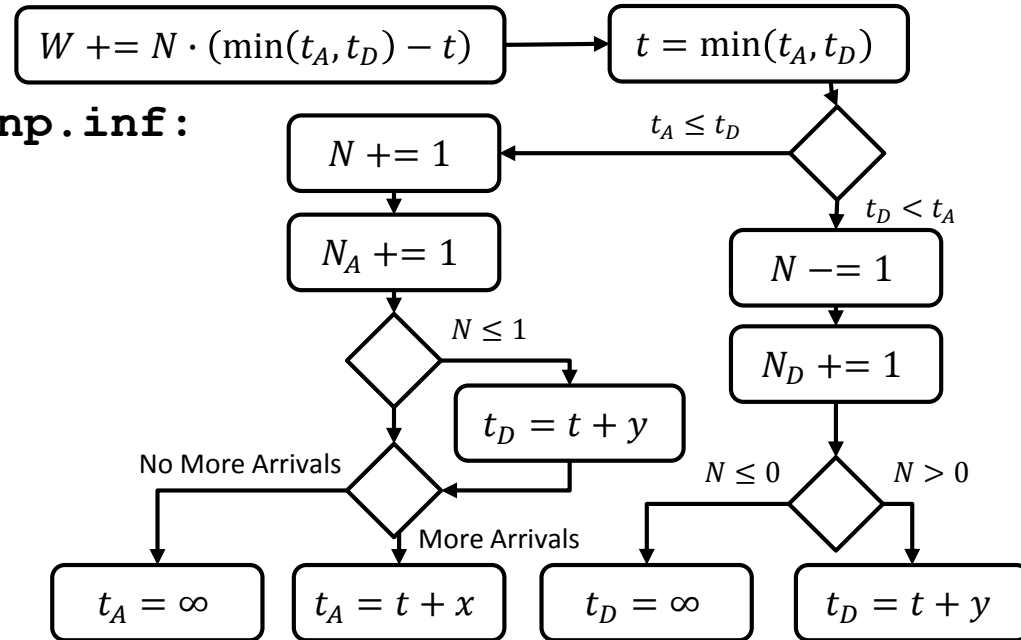
```
            t_A = t + generate_x() if t < 1000 else np.inf
```

```
    else:
```

```
        N -= 1
```

```
        N_D += 1
```

```
        t_D = t + generate_y() if N > 0 else np.inf
```



# Discrete Event Simulation



## Strengths

- Generate random variables exactly when needed
  - Function of time/state
- Scales well to many types of events
- Only need state from previous time step

## Limitations

- Difficult to calculate time-average results (need counter variables)
- State updates can be complex for atomic functions (Excel)



# DES World Views



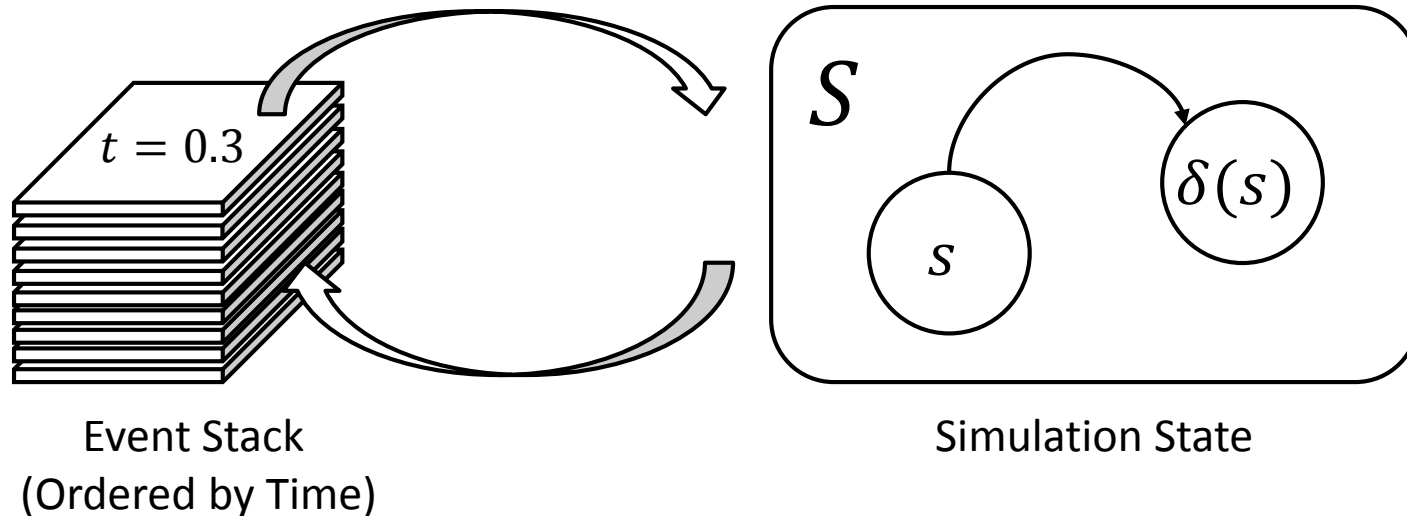
# DES World Views



- Three common types of simulation strategies in discrete event simulation (DES):
  - Event-Scheduling
  - Activity Scanning
  - Process Interaction
- Each matches a particular view for how the world works (i.e. world view)

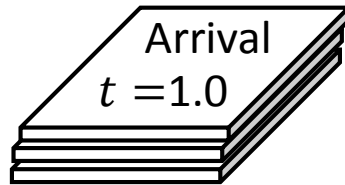
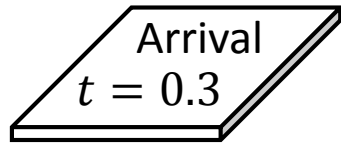
# Event-Scheduling World View

- **Events** are building blocks
- Schedule all events in an event stack
- Event execution performs state transition

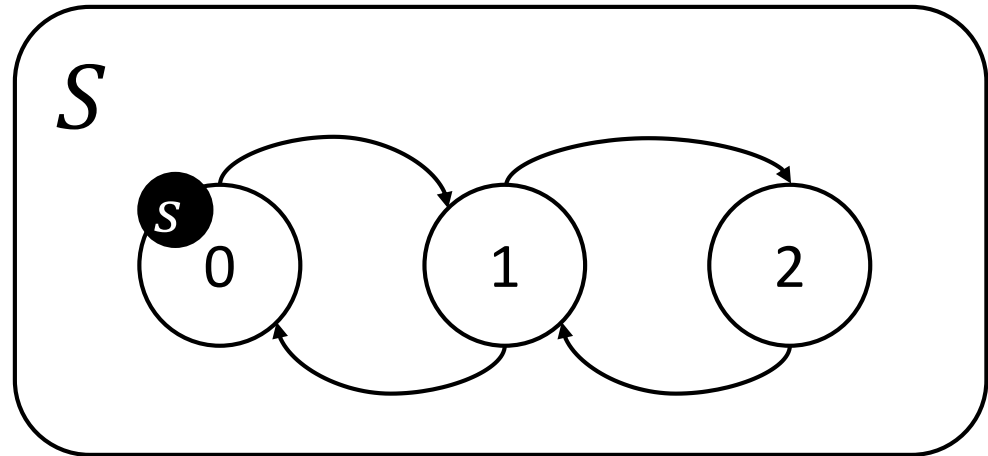




# Event-Scheduling Example



$t = 0.3$     $t = 1.0$     $t = 1.2$     $t = 1.7$





# Activity Scanning World View

- **Activities** are building blocks
- Define a sequence of activities waiting to be executed with required conditions
- Scan for activities at each time step

## Activity 1

- Precondition 1a
- Precondition 1b
- Duration
- Postcondition 1a
- Postcondition 1b

## Activity 2

- Precondition 2a
- Precondition 2b
- Duration
- Postcondition 2a
- Postcondition 2b

# Activity Scanning Example

## Inter-arrival 1

- Duration: 0.3
- Post:  $\delta(s) = s + 1$

## Inter-arrival 2

- Pre: Inter-arrival 1 complete
- Duration: 0.7
- Post:  $\delta(s) = s + 1$

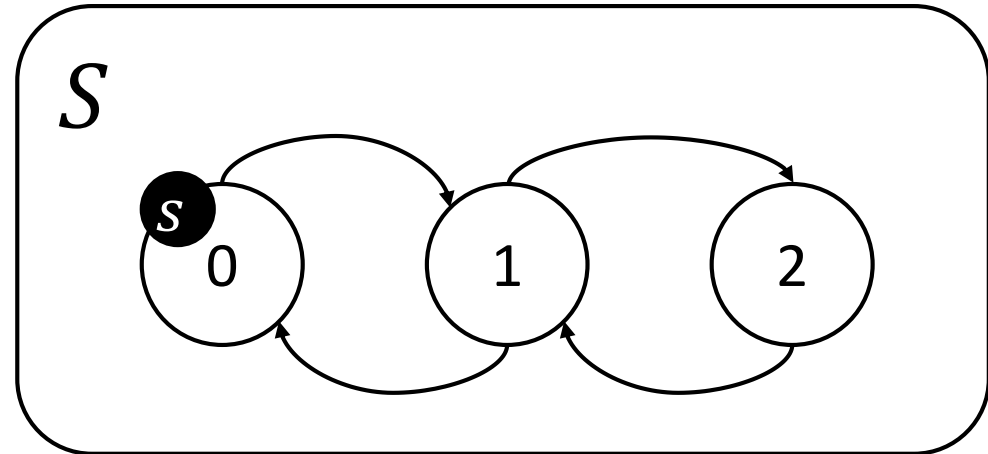
## Service 1

- Pre: Inter-arrival 1 complete
- Duration: 0.9
- Post:  $\delta(s) = s - 1$

## Service 2

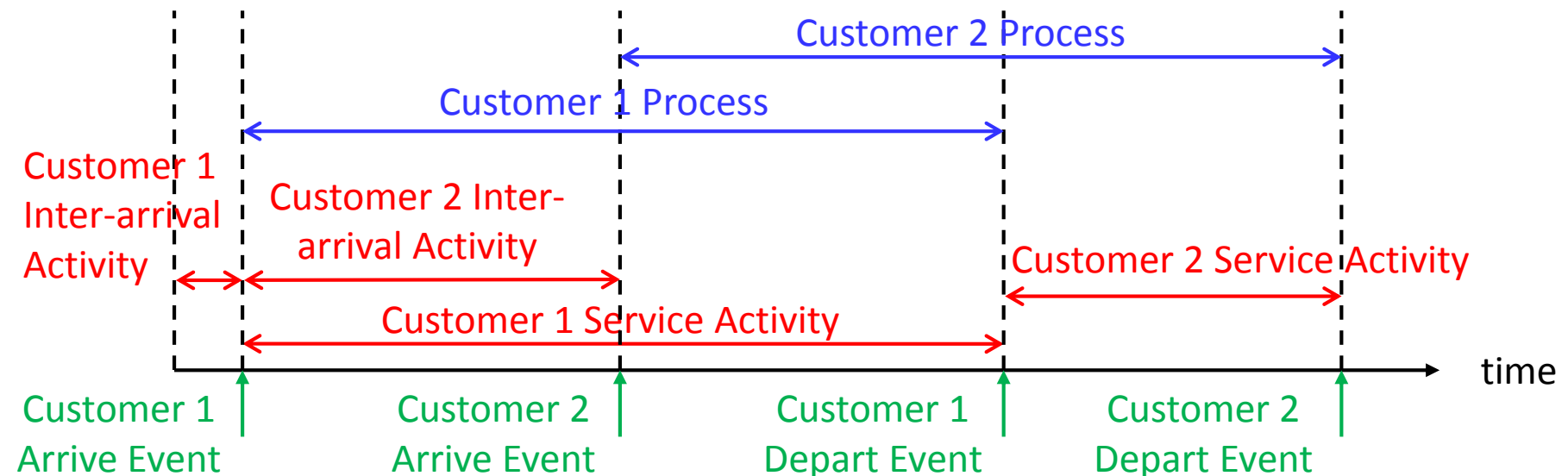
- Pre: Service 1 complete
- Pre: Inter-arrival 2 complete
- Duration: 0.5
- Post:  $\delta(s) = s - 1$

$t = 0.3$     $t = 1.0$     $t = 1.2$     $t = 1.7$



# Process Interaction World View

- **Processes** are building blocks
- Analogous to processes in an operating system
- Define a sequence of actions for the life-cycle of each model component



# Process Interaction Example



## Customer 1

- Arrive at 0.3
- Request server resource
- Hold resource for 0.9
- Release server resource
- Depart

## Customer 2

- Arrive at 1.0
- Request server resource
- Hold resource for 0.5
- Release server resource
- Depart

$t = 0.3$     $t = 1.0$     $t = 1.2$     $t = 1.7$

