

#### **Queuing Theory**

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Engineering Systems and Design

# **Queuing Systems**

- A system having a service facility at which units of some kind arrive for service; whenever there are more units in the system than the service facility can handle simultaneously, a queue (or waiting line) develops.
- In simple terms, a queuing system consists of a demand source, a queue and a service facility with one or more identical parallel servers
- A queuing network is a set of interconnected queuing systems



# **Queuing Theory**

- Queuing Theory is concerned with the behavior of waiting lines (delays/congestion)
- Fundamental parameters of a queuing system:
  - Demand Rate

Probability distribution of demand inter-arrival times

• Service Rate

- Probability distribution of service times
- Queue discipline (FCFS, SIRO, priorities, etc).



### **Kendal Notation**



### Little's Law

L = expected number of users in queueing system (those in queue plus those receiving service)

 $L_q = expected$  number of users in queue

W = expected time in queing system per user
 (waiting time plus service time)

 $W_q = expected$  time in queue per user

$$W = W_q + 1/\mu$$
  $L = L_q + \lambda/\mu$   
 $L_q = \lambda W_q$   $L = \lambda W$ 

Obtain one of the performance measures, the other three can be computed

# Important Result from Queueing Theory



### **Steady-state Conditions**

- Rho = ratio of demand rate vs service rate
- As loads on system increase, average waiting time increases exponentially
- Practical capacity = less than throughput capacity due to excessive delays
- Note that graph is for steady state conditions



Rho = 1.0

# Waiting Time

# **Example – Vaccination Stalls**

- We aim to compute the minimum number of stalls required in a vaccination centre\*.
- The service rate per stall is about 30 services per hour
- Minimum number of stalls to open?



Time	Demand
04:00	0
05:00	0
06:00	40
07:00	320
08:00	1120
09:00	2280
10:00	2480
11:00	2480
12:00	2160
13:00	1880
14:00	2240
15:00	2440
16:00	2760
17:00	3200
18:00	2600
19:00	1680
20:00	960
21:00	320
22:00	40
23:00	0

# Example – Vaccination Stalls

- We aim to compute the minimum number of stalls required in a vaccination centre\*. Time
- The service rate per stall is about 30 services per hou
- Minimum number of stalls to open?



Demand

0

0

40

0

04:00

05:00

06:00

#### Example – Steady State Results

			Q Model
Time	Dem.	Min Check-in	Expected Time in System (min)
04:00	0	0	0
05:00	0	0	0
06:00	40	2	3.6
07:00	320	11	7.32
08:00	1120	38	4.63
09:00	2280	77	3.74
10:00	2480	83	7.74
11:00	2480	83	7.74
12:00	2160	73	3.73
13:00	1880	63	7.7
14:00	2240	75	7.72
15:00	2440	82	4.74
16:00	2760	93	3.76
17:00	3200	107	7.77
18:00	2600	87	7.74
19:00	1680	57	3.7
20:00	960	33	3.61
21:00	320	11	7.32
22:00	40	2	3.6
23:00	0	0	0



I –	$P_0I$	sρ
$L_q$ –	$\overline{S!(1 - S)}$	$(-\rho)^2$

## Non-stationary Conditions

- However, it is important to recognize that queues in many systems:
  - Build up over time (nonstationary state)
  - Demand patterns are not constant over the day
  - First arrivals get no delay, later arrivals join growing queue



# Non-Stationary Queuing Systems

- Many service and production systems operate under dynamic conditions. These systems are often named as non-stationary queueing systems, as steady state conditions are never achieved.
- A characteristic trait of these systems is that the demand rate may exceed the service capacity at certain periods of the day - temporal overloading.
- During overloaded periods queues build up overloaded periods must be followed by periods of low demand to ensure that queues return to acceptable levels.
- Complex simulations models are often utilized to analyse and optimize the performance of these systems. However, optimization is generally difficult and time consuming due to the large number of variables that can be adjusted by decision-makers

## Non-Stationary Queuing Systems

- Examples of non-stationary queueing systems can be found everywhere: aviation systems (check-in, security checkpoints, flight scheduling); healthcare systems (resource and staff allocation), transportation systems (crew and fleet allocation), logistic systems (delivery management), manufacturing systems (production management), computer systems (server allocation), etc.
- COVID vaccination centres are a recent example of a time-dependent, nonstationary queueing system – demand and capacity vary considerably across different periods of the day – health officials need to manage the number of slots to make available per hour (demand rate control); and the number of staff required in the vaccination centres (service rate control); by considering the typical demand patterns (e.g. most people prefers to be vaccinated early or later in the day).

### **Simulation Models**

- Steady-state equations are not valid in non-stationary queues
- We can use simulation models to mimic queues and optimize service and demand rates

#### Leading Edge Simulation

JaamSim is a free and open source discreteevent simulation software which includes a drag-and-drop user interface, interactive 3D graphics, input and output processing, and model development tools and editors.

Available for Windows, MacOS, and Linux

License: JaamSim is Apache 2.0



**Download JaamSim** 

Source: https://jaamsim.com/

Tutorial: <a href="https://www.youtube.com/watch?v=8DhFtfxZV0A">https://www.youtube.com/watch?v=8DhFtfxZV0A</a>

#### **Discrete- Event Simulation – Steady State**

Input Editor ExponentialDistribution1

#### Key Inputs Graphics

Keyword	Default	Value
AttributeDefinitionList	None	
CustomOutputList	None	
UnitType	None	TimeUnit
RandomSeed	None	1
MinValue	0.0 h	0 s
MaxValue	Infinity h	
Mean	2.777777777777	1.125 s



Input Editor - ExponentialDistribution2

#### Key Inputs Graphics

Keyword	Default	Value
AttributeDefinitionList	None	
CustomOutputList	None	
UnitType	None	TimeUnit
RandomSeed	None	2
MinValue	0.0 h	0 s
MaxValue	Infinity h	
Mean	2.777777777777	120 s

30 Pax/hour= 1 Pax every 120 sec

#### 3200 Pax/hour= 1 Pax every 1.125 sec

### **Discrete- Event Simulation – Steady State**

Avg. Time in the System (min)



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### Example – Steady State Results

		Min Chook	Q Model	JaamSim
Time	Dem.	in	Expected Time in System (min)	Expected Time in System (min)
04:00	0	0	0	0
05:00	0	0	0	0
06:00	40	2	3.6	3.59
07:00	320	11	7.32	7.82
08:00	1120	38	4.63	4.88
09:00	2280	77	3.74	3.88
10:00	2480	83	7.74	8.09
11:00	2480	83	7.74	8.09
12:00	2160	73	3.73	3.85
13:00	1880	63	7.7	8.55
14:00	2240	75	7.72	8.73
15:00	2440	82	4.74	5.12
16:00	2760	93	3.76	3.98
17:00	3200	107	7.77	8.44
18:00	2600	87	7.74	8.27
19:00	1680	57	3.7	3.83
20:00	960	33	3.61	3.67
21:00	320	11	7.32	7.82
22:00	40	2	3.6	3.59
23:00	0	0	0	0

#### **Discrete- Event Simulation – NSS Conditions**



#### **NS Conditions - Results**

#### Input Editor - EntityProcessor1

Keyword	Default	Value
Trace	FALSE	
AttributeDefinitionList	None	
CustomOutputList	None	
NextComponent	None	EntityConveyor2
StateAssignment	None	
WaitQueue	None	Queue1
Match	None	
ResourceList	None	
NumberOfUnits	{1.0 }	
Capacity	1.0	10000
ServiceTime	0.0 h	ExponentialDistribution2

Open an Infinite Number of Servers

#### Avg. Time in the System (min) 2.13

#### Max. Time in the System (min) 30.99



#### Input Editor - EntityProcessor1

	Theorem	Mainternance	ronnac	Graphics
Keyword		Default	t	Value
Trace		FALSE		
AttributeDe	efinitionList	None		
CustomOut	putList	None		
NextCompo	onent	None		EntityConveyor2
StateAssign	nment	None		
WaitQueue	•	None		Queue1
Match		None		
ResourceLis	st	None		
NumberOfU	Jnits	{ 1.0	}	
Capacity		1.0		107
ServiceTime	e	0.0 h		ExponentialDistribution

the entire day

Avg. Time in the System (min) 2.20

Max. Time in the System (min) 30.99



Under steady state conditions, the model predicts 8.88 mins of avg. Time in the system

#### **NS Conditions - Results**

#### Input Editor - EntityProcessor1

Maintenance	Format Graphics
Default	Value
FALSE	
None	
None	
None	EntityConveyor2
None	
None	Queue1
None	
None	
{1.0 }	
1.0	90
0.0 h	ExponentialDistribution2
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	×
	Maintenance  Perfault  FALSE  None None None None None None None Non

Open 90 serves across the entire day

#### Avg. Time in the System (min) 4.35

#### Max. Time in the System (min) 40.08



#### **NS Conditions - Results**

#### Avg. Time in the System (min) 10.52

#### Max. Time in the System (min) 63.06



#### Input Editor - EntityProcessor1

tey inputs Th	nresholds	Main	ntenance Format		Graphics	
Keyword			Default		Value	
Trace			FALSE			
AttributeDefin	itionList		None			
CustomOutput	tList		None			
NextCompone	nt		None		EntityConveyor2	
StateAssignme	ent		None			
WaitQueue			None		Queue1	
Match			None			
ResourceList			None			
NumberOfUnit	s		{1.0 }			
Capacity			1.0		80	
ServiceTime			0.0 h		ExponentialDistributio	

Open 80 serves across the entire day

### **NSS Conditions - Results**

#### Input Editor - EntityProcessor1

Keyword	Default	Value
Trace	FALSE	
AttributeDefinitionList	None	
CustomOutputList	None	
NextComponent	None	EntityConveyor2
StateAssignment	None	
WaitQueue	None	Queue1
Match	None	
ResourceList	None	
NumberOfUnits	{1.0 }	
Capacity	1.0	70
ServiceTime	0.0 h	ExponentialDistribution2

Open 70 serves across the entire day

#### Avg. Time in the System (min) 41.85

#### Max. Time in the System (min) 136.28



### **NS Conditions - Results**



- This analysis only shows part of the optimization process of non-stationary systems
  - What about having a variable number of servers across the day (no need to have 100 stalls open during the entire day)
  - What about controlling the arrival demand by imposing slot limits (such as in vaccination centres, slot times are assigned to people)?

**Multi-Objective Problem** aiming to optimize 3 main objectives: level of service (e.g. minimize waiting time); demand acceptance rate (minimize demand displacement); service costs (minimize the number of servers to open per hour)



#### Capacity Management in Non-Stationary Queuing Systems – NSGA II

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## **Capacity Management**

**Capacity management** is the field of research that aims to optimize infrastructure operations while having "just enough" resources required to run applications and services without interruptions in desired performance.

Two main capacity management strategies are implement:

- Increasing service capacity By investing on resource capacity more staff; more machines, more infrastructure, etc.
- Efficiently distributing demand By imposing limits on scheduling slot scheduling; demand rate control, etc.

### Airport Slot Allocation Case Study

- Airport infrastructure Capacity is fixed by the number of runways in the airport – for instance Changi Airport runway system have a capacity of around 10 arrival flights every 15 minutes.
- Slot allocation is used to efficiently distribute demand across the day
- Question: How many slots to make available per hour given airport capacity constraints (i.e. no. of runways) and airline's slot requests (i.e. slot times requested by the airlines to operate their flights)?
  - Two main objectives to optimize:
    - Minimize expected fight delays in the airport
    - Minimize slot displacement to the airlines
  - Decisions Variable
    - Number of slots to make available per hour

### **Airport Simulation**

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CAST Model "Runway\_1\_Changi\_final" X Analysis Model "My Analysis Model (3)" X









Legend:

Requested demand

Allocated demand

- Slot Limit

---- Expected average delays

#### **Simulation Model**

### **Genetic Algorithm**

#### **Chromosome encoding**



#### NSGA-II – After 1 hour of Computation



### Recall: NSGA-II



### **Recall: Non-Dominated Sorting**



#### **Recall: Crowding Distance**



### NSGA-II – Pareto-Frontier



#### NSGA-II – Optimal Solutions

19 20 21 22 23 11 12 13 10 11 12 13 10 10 -25 -25 -25 -24 -25 -25 -24 -24 -25 -24 40 24 32 35 32 35 -35 -35 -35 -24 - 24 -30 -30 -30 37 30 -30 -25 -33 36 30 -33 



Legend:

# NSGA-II – Optimal Solutions

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### **NSGA-II – Optimal Solutions**



### **Declared Capacity Algorithm**





#### **Meta-Modeling**

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### Meta-Models

- It is well known that most of the time, in metaheuristics, the time-intensive part is the evaluation of the objective function.
- In many problems, the objective function is quite costly to compute (e.g. simulations).
- The alternative to reduce this complexity is to approximate the objective function and then replace the original objective function by its approximation function.
- This approach is known as meta-modeling

### **Airport Simulation**

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1 Hour of Computation to run 1 month of schedules – This invalidates the iterative process we aim to apply by using metaheuristics approaches

# Meta-modeling Techniques

- Many meta-modeling techniques may be employed for expensive objective functions. They are based on constructing an approximate model from a properly selected sample of solutions:
  - Analytical Approximations
  - Machine Learning Models
  - Neural Networks
  - Relaxed Simplified Model (e.g. ignore some constraints)
  - Model Decomposition
- There is a trade-off between the complexity of the model and its accuracy.

#### **Predicting Flight Delays**

Macroscopic Models

#### Markov-Chains + Queuing Theory

Delays are approximated using mathematical equations derived from Markov-chain theory





Microscopic Models

#### **CAST Simulation Tool**

delays to make predictions

Machine Learning Models

Analyses historical data of flight

Flight operations are simulated in very detail using agent-based simulation



#### Predicting Flight Delays

- We develop a random forest model to predict airport local delays by leveraging historic data from flight operations and meteorological conditions.
- Explanatory variables include: congestion indicators (no. arrivals, no. departures, congestion index, etc.), weather related variables (lightning count, wind speed, wind direction), queuing model predictions, time-of-the day dummy variables, etc.



#### **Predicting Flight Delays**

#### **CAST Simulation Model**

