Airside Congestion

Amedeo R. Odoni
T. Wilson Professor
Aeronautics and Astronautics
Civil and Environmental Engineering
Massachusetts Institute of Technology

Objectives
- Introduce fundamental concepts regarding airside delay

Topics
- The airport as a queuing system
- Dynamic behavior
- Long-term characteristics of airside delay
- Non-linearity
- Annual capacity of an airport
- Measuring delay

Reference: Chapters 11, 23
Delay Trends

OPSNET National Delays

Queues

- Queuing Theory is the branch of operations research concerned with waiting lines (delays/congestion)
- A queuing system consists of a user source, a queue and a service facility with one or more identical parallel servers
- A queuing network is a set of interconnected queuing systems
- Fundamental parameters of a queuing system:
  - Demand rate
  - Demand inter-arrival times
  - Utilization ratio
  - Capacity (service rate)
  - Service times
  - Queue discipline
Generic queueing system

Dynamic (“Short-Run”) Behavior of Queues

- Delays will occur when, over a time interval, the demand rate exceeds the service rate (“demand exceeds capacity”)
- Delays may also occur when the demand rate is less than the service rate -- this is due to probabilistic fluctuations in inter-arrival and/or service times (i.e., to short-term surges in demand or to slowdowns in service)
- These “probabilistic” (or “stochastic”) delays may be large if the demand rate is close to (although lower than) capacity over a long period of time
Dynamic Behavior of Queues [2]

1. The dynamic behavior of a queue can be complex and difficult to predict
2. Expected delay changes non-linearly with changes in the demand rate or the capacity
3. The closer the demand rate is to capacity, the more sensitive expected delay becomes to changes in the demand rate or the capacity
4. The time when peaks in expected delay occur may lag behind the time when demand peaks
5. The expected delay at any given time depends on the “history” of the queue prior to that time
6. The variance (variability) of delay also increases when the demand rate is close to capacity

Example of the Dynamic Behavior of a Queue

Expected delay for four different levels of capacity
(R1 = capacity is 80 movements per hour; R2 = 90; R3 = 100; R4 = 110)
Case of LaGuardia (LGA)

- **Since 1969:** Slot-based High Density Rule (HDR)  
  - DCA, JFK, LGA, ORD; “buy-and-sell” since 1985
- **Early 2000:** About 1050 operations per weekday at LGA
- **April 2000:** Air-21 (Wendell-Ford Aviation Act for 21st Century)  
  - Immediate exemption from HDR for aircraft seating 70 or fewer pax on service between small communities and LGA
- **By November 2000:** Airlines had added over 300 movements per day; more planned: virtual gridlock at LGA
- **December 2000:** FAA and PANYNJ implemented slot lottery and announced intent to develop longer-term policy for access to LGA
- **Lottery reduced LGA movements by about 10%; dramatic reduction in LGA delays**
- **June 2001:** Notice for Public Comment posted with regards to longer-term policy that would use “market-based” mechanisms
- **Process stopped after September 11, 2001; re-opened April 2002**

Scheduled aircraft movements at LGA before and after slot lottery

![Graph showing scheduled aircraft movements per hour at LGA](image)
Some Terminology for Queuing Systems

- Arrival of demands:
  \( x = \text{inter-arrival times} = \text{time between occurrence of successive demands} \); \( E(x) \); \( \sigma_x^2 \)
  \( \lambda = \text{"demand rate"} = \text{expected number of demands per unit of time} \)
  \( \lambda = 1 / E(x) \)

- Service times at the system:
  \( t = \text{inter-arrival times} = \text{time between occurrence of successive demands} \); \( E(t) \); \( \sigma_t^2 \)
  \( \mu = \text{"demand rate"} = \text{expected number of demands per unit of time} \)
  \( \mu = 1 / E(t) \)
The "utilization ratio", \( \rho \), measures the intensity of use of a queuing system

\[
\rho = \frac{\text{demand rate}}{\text{service rate}} = \frac{\text{"demand"}}{\text{"capacity"}} = \frac{\lambda}{\mu}
\]

A queuing system cannot be operated in the long run with a utilization ratio which exceeds 1, since the longer the system is operated, the longer the queue length and waiting time will become. Thus, a queuing system will be able to reach a long-term equilibrium ("steady state") in its operation, only if \( \rho < 1 \), in the long run.

For queuing systems that reach steady state the expected queue length and expected delay are proportional to:

\[
\frac{1}{1 - \rho}
\]

Thus, as the demand rate approaches the service rate (or as \( \rho \to 1 \), or as "demand approaches capacity") the average queue length and average delay increase rapidly.
Delay vs. Demand/Capacity

High Sensitivity of Delay at High Levels of Utilization
### Four Major Measures of Performance

*With system in equilibrium ("steady state"):*

- \( L_q = \text{expected no. of customers in queue} \)
- \( W_q = \text{expected waiting time in queue} \)
- \( L = \text{expected no. of customers in system} \) (includes those waiting and those receiving service)
- \( W = \text{expected total time in system} \) (waiting time plus time in service)

### Relationships among the Four Measures in Steady-State

\[
W = W_q + E[t] = W_q + \frac{1}{\mu} \quad \text{(1)}
\]

[Note: (1) makes intuitive sense]

\[
L_q = \lambda W_q \quad \text{(2)}
\]

\[
L = \lambda W \quad \text{(3)}
\]

[Note: (2) and (3) are far less obvious and are known as “Little’s formulae”.]
An Important Result: The “P-K formula”

For queuing systems with Poisson demands, ANY type of service time, one server and infinite queuing capacity (M/G/1 system):

\[ W_q = \frac{\lambda \left[ \left( \frac{1}{\mu} \right)^2 + \sigma_t^2 \right]}{2(1 - \rho)} = \frac{\lambda \left( E^2(t) + \sigma_t^2 \right)}{2(1 - \rho)} \]

Assumes steady-state conditions: \( \rho < 1 \) (\( \lambda < \mu \))

Dependence on Variability (Variance) of Demand Inter-Arrival Times and of Service Times
Runway Example

- Single runway, mixed operations
- \( E[t] = 75 \) seconds; \( \sigma = 25 \) seconds
  \[ \mu = \frac{3600}{75} = 48 \] per hour
- Assume demand is relatively constant for a sufficiently long period of time to have approximately steady-state conditions
- Assume Poisson process is reasonable approximation for instants when demands occur

Estimated expected queue length and expected waiting time

<table>
<thead>
<tr>
<th>( \lambda ) (per hour)</th>
<th>( \rho )</th>
<th>( L_q )</th>
<th>( L_q ) ( % ) change</th>
<th>( W_q ) (seconds)</th>
<th>( W_q ) ( % ) change</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>0.625</td>
<td>0.58</td>
<td></td>
<td>69</td>
<td></td>
</tr>
<tr>
<td>30.3</td>
<td>0.63125</td>
<td>0.60</td>
<td>3.4%</td>
<td>71</td>
<td>2.9%</td>
</tr>
<tr>
<td>36</td>
<td>0.75</td>
<td>1.25</td>
<td></td>
<td>125</td>
<td></td>
</tr>
<tr>
<td>36.36</td>
<td>0.7575</td>
<td>1.31</td>
<td>4.8%</td>
<td>130</td>
<td>4%</td>
</tr>
<tr>
<td>42</td>
<td>0.875</td>
<td>3.40</td>
<td></td>
<td>292</td>
<td></td>
</tr>
<tr>
<td>42.42</td>
<td>0.88375</td>
<td>3.73</td>
<td>9.7%</td>
<td>317</td>
<td>8.6%</td>
</tr>
<tr>
<td>45</td>
<td>0.9375</td>
<td>7.81</td>
<td></td>
<td>625</td>
<td></td>
</tr>
<tr>
<td>45.45</td>
<td>0.946875</td>
<td>9.38</td>
<td>20.1%</td>
<td>743</td>
<td>18.9%</td>
</tr>
</tbody>
</table>

Can also estimate PHCAP \( \approx 40.9 \) per hour
Variability of Queues

• The variability of delay also builds up rapidly as demand approaches capacity.
• In “steady state” the standard deviation -- a measure of variability -- of delay and of queue length is also proportional to
  \[
  \frac{1}{1 - \rho}
  \]
• A large standard deviation implies unpredictability of delays from day to day and low reliability of schedules

Estimating Delays at an Airport

• The estimation of delays at an airport is usually sufficiently complex to require use of computer-based models
  _ Queuing models: solve numerically the equations describing system behavior over time
  _ Simulation models
• For very rough approximations, simplified models may sometimes be useful
  _ Steady-state queuing models
  _ Cumulative diagrams
Steps in an Airside Capacity/Delay Analysis

1. Identify all available runway configurations.
2. Compute the (maximum throughput) capacity of each configuration.
3. Prepare the capacity coverage chart for the airport and understand true utilization of various configurations.
4. Develop typical demand profiles for the number of runway movements in a day.
5. Compute delays for typical combinations of demand and available capacity over a day.
6. Draw conclusions based on the above.

Annual Airside Capacity

- The number of aircraft movements that can be handled at a reasonable level of service in one year
- Vaguely defined, but very important for planning purposes
- Runway system is typically the limiting element
- Estimation of annual capacity must consider
  - Typical hourly (saturation) capacity
  - Pattern of airport use during a day
  - Reasonable level of delays during busy hours of day
  - Seasonal and day-of-the-week peaking patterns of demand
Annual Airside Capacity: Boston Example

1. Typical hourly runway capacity (based on CCC) = 115.
   Compute: \( A = 115 \times 24 \times 365 = 1,007,400 \)
2. Equivalent of \(~16-17\) hours of strong activity per day.
   Compute: \( 1,007,400 \times (16/24) = 671,600 \)
3. \(~85\%\) utilization in busy hours for (barely) tolerable delays
   Compute: \( 671,600 \times 0.85 = 570,860 \)
4. Summer season days have about 15\% more movements than winter season days
   \( (570,860 / 2) + (570,860 / 2) \times (1/ 1.15) = 534,000 \)
This is a rough estimate of the ultimate capacity of Logan airport, without expansion of capacity

The capacity coverage chart for Boston/Logan

![Capacity Coverage Chart](chart.png)
Peaking Characteristics of 80 Airports in ACI Survey (1998)

<table>
<thead>
<tr>
<th>Total annual pax (million)</th>
<th>Sample size</th>
<th>Average monthly peaking ratio*</th>
<th>Range of monthly peaking ratios</th>
<th>Monthly peaking ratios greater than 1.2</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt;20</td>
<td>23</td>
<td>1.18</td>
<td>1.09 – 1.43</td>
<td>6 of 23 (26%)</td>
</tr>
<tr>
<td>10 – 20</td>
<td>13</td>
<td>1.25</td>
<td>1.08 – 1.55</td>
<td>9 of 13 (69%)</td>
</tr>
<tr>
<td>1 – 10</td>
<td>44</td>
<td>1.35</td>
<td>1.11 – 1.89</td>
<td>34 of 44 (77%)</td>
</tr>
</tbody>
</table>

* Monthly peaking ratio = (average number of passengers per day during peak month) / (average number of passengers per day during entire year)

Estimating Annual Capacity: Generalization

Let C be the typical saturation capacity per hour of airport X and let

\[ A = C \times 24 \times 365 = C \times 8760 \]

Then the annual capacity of X will be in the range of 50%-60% of A, the percentage depending on local conditions of use and peaking patterns.

Note: If instead of saturation capacity, C is the declared capacity, then the annual capacity will be in the range of 60%-70% of A, since the declared capacity is usually set to approximately 85%-90% of saturation capacity.
Difficulty in Validating Delay Estimates for the Most Important Instances of Congestion

- It is extremely difficult to use field data to validate queuing models (or simulations) when congestion is severe
- Tightly inter-connected, complex system
- Users react dynamically to delays (feedback effects, flight cancellations)
- Geographical spreading (no single location for measurement), temporal propagation and secondary effects
- Delay-free, nominal travel times hard to come by
- Causality is unclear

Scheduled Flight Duration Includes “Hidden Delay”

- In the US a flight is counted as “late” if it arrives at the gate more than 15 minutes later than scheduled
- In recognition of habitual delays, airlines have been lengthening the scheduled duration of flights
  - improve “on-time arrival” statistics
  - improve reliability of their schedules
- Thus, a flight that arrives on schedule may in truth have been significantly delayed!
“Hidden Delay” May Be Very Large

Airfield Delay: Some Points for Planning

- The relationship between demand and capacity, on one hand, and delay, on the other, is highly nonlinear
- Serious delays may occur even when average demand is less than (but close to) capacity
- If demand is close to capacity in good weather conditions, then large delays will occur under worse conditions
- When demand exceeds 85-90% of typical capacity for extended parts of the day, then both average delay and the variability of delay will be large
- Attribution of delays to specific causes is extremely difficult