Generating probabilistic capacity scenarios from weather forecast: A design-of-experiment approach

Gurkaran Singh Buxi
Mark Hansen
Overview

1. Introduction & motivation
2. Current practice & literature review
3. Air Traffic Flow Management (ATFM) model
4. Generating probabilistic capacity scenarios
5. Design-of-experiments
6. Results and future work
Introduction & motivation

- Air traffic demand is anticipated to increase
- National Aviation System (NAS) infrastructure is operating at near capacity
  - Delays in the NAS are likely to increase
  - Weather is the largest contributor to delays
- Strategic decisions take place around 2 hours in advance

![Causes of NAS delay graph](SOURCE: Bureau of Transportation Statistics and FAA OPSNET)
Introduction & motivation

Delay reduction in the National Aviation System

- Provide good weather capacity in bad weather
- Increase infrastructure capacity
- Better navigation and equipment
- Decrease current operations
- Improve decision making under weather uncertainty

Improve decision making under weather uncertainty

- Research focuses on a terminal
- Terminal arrival capacity is stochastic and dependant on several weather variables
- Weather provides a foundation for terminal capacity prediction
Introduction & motivation

Research goal

Improve the service provider’s strategic decision making by effectively utilizing the day-of-operations weather forecasts

Research objectives

Develop probabilistic capacity scenarios using the day-of-operations weather forecast.

Develop a methodology to assess the performance of the probabilistic capacity scenarios
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6. Results and future work
Current practice uses judgment, experience and stakeholder’s preferences.

No formal mechanism to address the uncertainty associated with the forecast.
Literature review on ATFM models

Existing framework in literature

Uncertainty in the terminal capacity

Demand and cost ratio ($\lambda$)

Air Traffic Flow Management (ATFM) models

Strategic decisions
- Air delays
- Ground delays
Literature review on terminal capacity uncertainty

Uncertainty at terminal capacity is represented by multiple time series of capacity associated with a probability (prob. capacity scenarios)

Scenarios

- Operations Research (OR) and finance community
- Model the possible future evolution of a random variable
- Associated with a probability of occurrence
Literature review on terminal capacity uncertainty

Uncertainty at terminal capacity is represented by multiple time series of capacity associated with a probability (prob. capacity scenarios)

**Scenarios**

- Operations Research (OR) and finance community
- Model the possible future evolution of a random variable
- Associated with a probability of occurrence

**In Air Traffic Flow Management (ATFM)**

- Random variable is *terminal arrival capacity, Airport Acceptance Rate (AAR)*
- A time series of AAR values associated with a probability
- Inputs into an ATFM model that minimize expected delay costs
Literature review on terminal capacity uncertainty

Probabilistic capacity scenarios used in Air Traffic Flow Management (ATFM) models

Artificial data, for illustrative purposes

ATFM models
- Cook & Wood
- Richetta & Odoni
- Mukherjee & Hansen
- Ball et al.
Literature review on terminal capacity uncertainty

Probabilistic capacity scenarios generated from capacity data

Kmeans clustering on the historical AAR capacity

No current methodology uses the weather forecast to develop specific day-of-operation probabilistic capacity scenarios
Contribution to literature

Weather forecasts + historical capacity data

Probabilistic capacity scenarios

Demand and cost ratio ($\lambda$)

Air Traffic Flow Management (ATFM) models

Strategic decisions
- Air delays
- Ground delays
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Air Traffic Flow Management model

- Static Stochastic Ground Delay Model (SSGDM)
  - Plans efficient ground delays for the terminal airport
  - Decisions once made can not be revised as more information is revealed
- Compatible in Collaborative Decision Making (CDM) environment
  - Determines an arrival rate for the airport
  - Enables Ration by schedule.
  - Allows substitution, cancellation and compression
- Requires probabilistic capacity scenarios as inputs
  - Basis for validating the scenarios which are developed
Static Stochastic Ground Delay Model

Determines optimal ground delay decisions
Requires probabilistic capacity scenarios and demand
Static Stochastic Ground Delay Model

Ground delay (GD) taken by the flights at the origin airport
Static Stochastic Ground Delay Model

Airborne delay (AD1) due to insufficient capacity in Scenario 1. Occurs with probability P1.
Static Stochastic Ground Delay Model

- Scheduled arrivals
- Probabilistic capacity scenario1 (Prob: P1)
- Probabilistic capacity scenario2 (Prob: P2)
- Planned Airport Arrival Rate (PAAR)

No air delay in scenario 2!!
Occurs with probability P2
Theoretical delay cost = $GD + \lambda E(AD) = GD + \lambda (AD1 \times P1 + 0 \times P2)$
Static Stochastic Ground Delay Model

Key Contributions

• To determine capacity scenarios and probabilities from historical capacity data and weather forecasts

• Method of assessing the performance of the scenarios in real world application
Static Stochastic Ground Delay Model

Method of assessing the performance of the scenarios in real world application

1. Consider a historical day and assume we have developed the scenarios for that day

2. Using the demand and the scenarios, determine the PAAR from the SSGDM

3. Recall the SSGDM outputs the PAAR (efficient ground delays and expected air delay)
4. Since it is a *historical* day, we know the *realized capacity* on that day at the airport.

*(Equivalent to saying that today we know yesterday’s capacity, i.e. we know the historical capacity but DO NOT know today’s capacity)*
Static Stochastic Ground Delay Model

Method of assessing the performance of the scenarios in real world application

4. Since it is a historical day, we know the realized capacity on that day at the airport.

5. We can determine the realized air delays using a simple queuing model between PAAR and the realized capacity.
Static Stochastic Ground Delay Model

Method of assessing the performance of the scenarios in real world application

Realized total delay cost (TC) = Ground Delay + λ * RAD

We assess the performance of the scenarios using the realized total delay cost (TC)
Static Stochastic Ground Delay Model

Method of assessing the performance of the scenarios in real world application

Based on ‘n’ historical days. Demand, weather forecast and realized capacity is available.

Day 1
Weather forecast

Day 2
Weather forecast

Day 3
Weather forecast

....

Day n
Weather forecast
Static Stochastic Ground Delay Model

Method of assessing the performance of the scenarios in real world application

Based on ‘n’ historical days. Demand, weather forecast and realized capacity is available.

Day 1
Weather forecast

Day 2
Weather forecast

Day 3
Weather forecast

....

Day n
Weather forecast

Scenario generation

Future

Value

Time

Scenario 1 (Prob: P1)
Scenario 2 (Prob: P2)
Scenario 3 (Prob: P3)
Static Stochastic Ground Delay Model

Method of assessing the performance of the scenarios in real world application

Based on ‘n’ historical days. Demand, weather forecast and realized capacity is available.

Scenario generation
Static Stochastic Ground Delay Model

Method of assessing the performance of the scenarios in real world application

Based on ‘n’ historical days. Demand, weather forecast and realized capacity is available.

Day 1
- Weather forecast

Day 2
- Weather forecast

Day 3
- Weather forecast

....

Day n
- Weather forecast

Scenario generation

Static Stochastic Ground Delay Model

Demand

Realized capacity

Realized total costs

Realized total costs

Realized total costs

Realized total costs
Static Stochastic Ground Delay Model

Method of assessing the performance of the scenarios in real world application

Based on ‘n’ historical days. Demand, weather forecast and realized capacity is available.

Day1
Weather forecast

Day2
Weather forecast

Day3
Weather forecast

....

Day n
Weather forecast

Scenario generation

Demand

Realized capacity

Realized total costs

Realized total costs

Realized total costs

Realized total costs

Average realized total cost
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Generating probabilistic capacity scenarios

Four US Airports: SFO, LAX, BOS, ORD

Months: May, June, July, August and September


Number of historical days (N): ≈450

Time duration: 7am – 10 pm (total of 60, 15 minute periods)

Using the weather forecasts issued for the airport between 5 am -7 am
Developed *five* methodologies for SFO to generate probabilistic capacity scenarios

<table>
<thead>
<tr>
<th>Number</th>
<th>Methodology</th>
<th>Historically realized capacity</th>
<th>Weather Forecast</th>
<th>Additional reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Perfect Information</td>
<td>✗</td>
<td>✗</td>
<td>Benchmark</td>
</tr>
<tr>
<td>2</td>
<td>Naïve Clustering</td>
<td>✓</td>
<td>✗</td>
<td>Benchmark</td>
</tr>
<tr>
<td>3</td>
<td>Stratus Binning (Unique for SFO)</td>
<td>✓</td>
<td>✓</td>
<td>STRATUS Forecast</td>
</tr>
<tr>
<td>4</td>
<td>TAF Clustering</td>
<td>✓</td>
<td>✓</td>
<td>Terminal Aerodrome Forecast</td>
</tr>
<tr>
<td>5</td>
<td>Dynamic Time Warping scenarios</td>
<td>✓</td>
<td>✓</td>
<td>Terminal Aerodrome Forecast</td>
</tr>
</tbody>
</table>
Generating probabilistic capacity scenarios

1. Perfect Information

- Predict exact capacity
- Probability is thus 1
- Best possible planning, lowest cost
- All potential delays are ground delays
Generating probabilistic capacity scenarios

2. No weather information, Naïve Clustering

Requires historical AAR data and no weather forecast data

Scenarios are representative AAR profiles for days that have similar capacity

The probability of a scenario is proportional to the number of days which have similar AAR profiles
Generating probabilistic capacity scenarios

SFO Marine Stratus Forecast System (STRATUS)

- SFO experiences fog during the summer months
- Fog reduces visibility, in turn reducing landing capacity
- STRATUS forecast product exclusively for SFO
- Predicts the fog dissipation time: Fog “burn off” time
- Probabilities of fog burn off before 10am, 11am and 12 pm

<table>
<thead>
<tr>
<th>Date</th>
<th>Predicted burn off time</th>
<th>P(10)</th>
<th>P(11)</th>
<th>P(12)</th>
<th>Actual burn off</th>
</tr>
</thead>
<tbody>
<tr>
<td>6/17/2004</td>
<td>11:31</td>
<td>0.05</td>
<td>0.3</td>
<td>0.65</td>
<td>10:51</td>
</tr>
<tr>
<td>6/20/2004</td>
<td>11:07</td>
<td>0.1</td>
<td>0.45</td>
<td>0.8</td>
<td>11:51</td>
</tr>
</tbody>
</table>
Generating probabilistic capacity scenarios

3. Scenarios from STRATUS forecasts

A scenario is a representative capacity profile for actual fog burn off in a 15 minute period.

Probabilities are obtained from the day of operations STRATUS forecast.
Generating probabilistic capacity scenarios

Terminal Aerodrome Forecast (TAF)

KSFO 011121Z 011212 28006KT P6SM FEW010

TEMPO 1316 BKN010
FM1800 29010KT P6SM SCT200
FM2200 27018KT P6SM SCT200
FM0400 27010KT P6SM SKC

- Forecasts 7 metrological variables
- Forecasts conditions up to 24 hours into the future
- Forecast issued for all major US airports
Generating probabilistic capacity scenarios

5. Dynamic Time Warping (DTW) Scenarios

(Similar TAFs *should* have similar AAR profiles)

How similar is the day of operation TAF to the historical TAFs?

Note: DoO: Day of Operation
Generating probabilistic capacity scenarios

5. Dynamic Time Warping (DTW) Scenarios

- Developed for Speech Recognition
- Data mining technique, compares multidimensional features vectors
- Illustration
  - Capacity scenarios are thus the actual AAR profiles of days having similar TAF
  - The probabilities of the capacity scenarios are inversely proportional to the distance of the shortest path
Generating probabilistic capacity scenarios

5. Dynamic Time Warping (DTW) Scenarios

[Graph showing two lines labeled TS1 and TS2 against time and amplitude axes]
Generating probabilistic capacity scenarios

5. Dynamic Time Warping (DTW) Scenarios

\[ \text{Similarity (S)} \propto \frac{1}{\sum_{i=1}^{10} C_i^2} \]
Generating probabilistic capacity scenarios

5. Dynamic Time Warping (DTW) Scenarios

Controlling the degree of similarity by Dimension factor (DF)

"Dissimilar forecasts should be penalized more"

Similarity (S) \( \propto \frac{1}{\left( \sum_{i=1}^{10} C_i^2 \right)^{DF}} \)
Generating probabilistic capacity scenarios

5. Dynamic Time Warping (DTW) Scenarios

Controlling the number of scenarios: Minimum Probability ($P_{min}$)

“The probability of the least similar scenario should be greater than a minimum probability threshold”
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Design of experiments

Three variables influence similarity & warping, and number of scenarios

<table>
<thead>
<tr>
<th>Variable</th>
<th>Values</th>
<th>Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weighting factor (WF)</td>
<td>Low values</td>
<td>Selects days which have similar forecasts for different periods</td>
</tr>
<tr>
<td></td>
<td>High values</td>
<td>Selects days which have similar forecasts for similar periods</td>
</tr>
<tr>
<td>Dimension factor (DF)</td>
<td>Low values</td>
<td>Decreases sensitivity of scenario probability to forecast similarity</td>
</tr>
<tr>
<td></td>
<td>High values</td>
<td>Increases sensitivity of scenario probability to forecast similarity</td>
</tr>
<tr>
<td>Minimum probability (Pmin)</td>
<td>Low values</td>
<td>Selects more scenarios</td>
</tr>
<tr>
<td></td>
<td>High values</td>
<td>Selects fewer scenarios</td>
</tr>
</tbody>
</table>
Design of experiments

Scheduled arrivals and $\lambda$

3 variables: WF, DF and Pmin

DTW Scenarios
(Time = 20min)

Static Stochastic Ground Delay model
(Time = 3min)

PAAR

Capacity

Determine variables (WF, DF and Pmin) which minimize average realized total costs

Average realized total costs

Deterministic queuing model to determine RAD and realized total cost

(Time = seconds)
Design of experiments

Objective is to determine variables which **minimize** average realized total costs

**Optimization Problem:**

**Objective function**: Minimize average realized total costs

**Decision Variables (DV)**: WF, DF and Pmin

**Constraints**: All DV are $\geq 0$ and $\leq$ UB.

**Challenges**:  
Objective function has no algebraic functional form  
Expensive function evaluations (23 minutes for a single evaluation): No SA or GA  
Objective function might have multiple local minima
Design of experiments

Stochastic Response Surface Method
(Finds the global minima in a probabilistic sense)

Algorithm (Jones et al. 2001)
Step 0: Create and evaluate an initial combination of variable values
Step 1: Create a surrogate model using the evaluated points
Step 2: Select a new point using the surrogate model and evaluate it
Step 3: Go to step 1, unless a stopping criterion is met.

Step 0: Latin Hypercube sampling (sample to explore the objective function)

Step 1: Polynomial, Kriging, Smoothing splines, Loess (mimic the objective function)

Step 2: Balancing local and global searches (Key step)

Step 3: Stopping criterion
Design of experiments

When the algorithm terminates, it provides the lowest average total delay costs and the values of the three variables.
Design of experiments

Dynamic time warping scenarios for 6/23/2004

AAR vs Time

Scenario 1 (Prob 0.187) - Blue
Scenario 2 (Prob 0.186) - Red
Scenario 3 (Prob 0.183) - Green
Scenario 4 (Prob 0.182) - Purple
Scenario 5 (Prob 0.143) - Teal
Scenario 6 (Prob 0.116) - Orange
Realized AAR - Violet
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Results

• Results are based on 45 historical days
• For these historical days, we have the demand, the weather forecasts and the realized capacity
  (realized capacity is the capacity which was experienced at the airport on that day)
• Average total realized cost, is the realized total cost averaged over the 45 days
## Results

<table>
<thead>
<tr>
<th>Airport</th>
<th>PI</th>
<th>Naïve</th>
<th>TAF</th>
<th>DTW</th>
<th>STRATUS</th>
<th>(Naïve-DTW)/Naïve</th>
</tr>
</thead>
<tbody>
<tr>
<td>SFO</td>
<td>1447.5</td>
<td>3543.45</td>
<td>2916.75</td>
<td>2677.8</td>
<td>2733</td>
<td>25%</td>
</tr>
</tbody>
</table>

*Bold italics*: Statistically different from naïve at 0.1 level using a paired t – test

Weather forecast assist in planning of operations by lowering average realized costs.

DTW gives the lowest cost amongst methodologies requiring forecast.

DTW is 5% lower than STRATUS. TAF can assist in planning operations at other airports.

On average weather forecasts reduce cost by 25% for SFO.

Imperfect information is doubling the costs of ground delay.
# Results

<table>
<thead>
<tr>
<th>Airport</th>
<th>PI</th>
<th>Naïve</th>
<th>TAF</th>
<th>DTW</th>
<th>Stratus</th>
<th>(Naïve-DTW) /Naive</th>
</tr>
</thead>
<tbody>
<tr>
<td>SFO</td>
<td>1448</td>
<td>3543.5</td>
<td>2916.75</td>
<td>2677.8</td>
<td>2733</td>
<td>25%</td>
</tr>
<tr>
<td>LAX</td>
<td>306.15</td>
<td>621.6</td>
<td>626.25</td>
<td>573.9</td>
<td>-</td>
<td>9%</td>
</tr>
<tr>
<td>BOS</td>
<td>2942</td>
<td>9249.6</td>
<td>8550.3</td>
<td>6449.55</td>
<td>-</td>
<td>30%</td>
</tr>
<tr>
<td>ORD</td>
<td>12755</td>
<td>34801</td>
<td>33413</td>
<td>28996.5</td>
<td>-</td>
<td>17%</td>
</tr>
</tbody>
</table>

*Bold italics:* Statistically different from naïve at 0.1 level using a paired t-test
Results

<table>
<thead>
<tr>
<th>Airport</th>
<th>Design Parameters</th>
<th></th>
<th></th>
<th></th>
<th>No. of Scenarios</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WF</td>
<td>DF</td>
<td>Pmin</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SFO</td>
<td>1.57</td>
<td>0.79</td>
<td>.0023</td>
<td>350-400</td>
<td></td>
</tr>
<tr>
<td>BOS</td>
<td>6</td>
<td>2.5</td>
<td>.065</td>
<td>12-25</td>
<td></td>
</tr>
<tr>
<td>LAX</td>
<td>2</td>
<td>2.5</td>
<td>.055</td>
<td>12-22</td>
<td></td>
</tr>
<tr>
<td>ORD</td>
<td>4.74</td>
<td>2.27</td>
<td>.043</td>
<td>15-25</td>
<td></td>
</tr>
</tbody>
</table>

Designs are different for different airports
For Boston, forecast for a period is compared to forecasts for nearby periods
For Boston, LAX and Chicago scenario probability is more sensitive to TAF similarity when compared to SFO.
Optimal number of scenarios for SFO is higher than other airports
Results

Number of scenarios at the optimal design values

**SFO**

**ORD**
Results

Realized costs (DTW Scenarios) - Realized costs(Naïve Clustering) Vs Cost under PI

Cost under Perfect Information (ground delay min)

Capacity decreases
Cost (PI) increases
Results

Realized costs (DTW Scenarios) - Realized costs (Naïve Clustering) Vs Cost under PI

ORD

Capacity decreases
Cost (PI) increases

Cost under Perfect Information (ground delay min)
Results

- A much simpler technique
- Construct a single scenario using capacity percentiles for every time period
- Use this single scenario in the SSGHM and compares realized costs

![Bar chart showing the ratio of average realized cost (Percentile) to average realized cost (DTW) for ORD. The x-axis represents the percentile from 10th to 100th, and the y-axis shows the ratio ranging from 0 to 2.5. The chart indicates that the ratio decreases from risk-averse to highly optimistic.]
Results

- A much simpler technique
- Construct a single scenario using capacity percentiles for every time period
- Use this single scenario in the SSGHM and compares realized costs

![Graph showing cost under perfect information]

- Capacity decreases
- Cost (PI) increases
Conclusions

First research to generate probabilistic capacity scenarios from weather forecasts using several statistical methodologies.

Developed a platform where these strategies can be tested.

Demonstrated that scenarios generated with weather reduce the costs by 10%-30% in operations planning.

In general DTW gives the lowest average costs.

The cost of imperfect information is nearly double with respect to costs under perfect information.

Showed that TAF can offer similar level of benefit as STRATUS.
The end!
Backup
Generating probabilistic capacity scenarios

4. TAF Clustering

• Requires the historical TAFs and the historical realized capacity
• *Determine groups of days which have similar TAF forecasts*
• Scenarios are the representative AAR profiles for the days which have similar weather forecasts
• Probabilities are the fraction of the days which have similar AAR profiles within a similar weather group
4. TAF Clustering, scenarios for SFO

- A day of operation is classified according to its TAF in either one of the groups.
- Depending on the classification, the day would have either 2 or 3 scenarios.

![Graph showing TAF clusters for SFO with different probabilities and time series data.](image)
Static Stochastic Ground Delay Model

Method of assessing the performance of the scenarios in real world application

Realized total delay cost ≠ Theoretical delay cost

\[ \text{RAD} \neq \mathbb{E}(\text{AD}) \]

The realized capacity is a RV and never identical to any scenario
4. Dynamic Time Warping Scenarios (2/3)

Dynamic Time Warping

- Developed for Speech Recognition
- Data mining technique, compares multidimensional features vectors
- Illustration

Capacity scenarios are thus the actual AAR profiles of days having similar TAF.

The probabilities of the capacity scenarios are inversely proportional to the distance of shortest path.
4. Dynamic Time Warping Scenarios (3/3)

<table>
<thead>
<tr>
<th>[TAF]_1</th>
<th>D_1</th>
</tr>
</thead>
<tbody>
<tr>
<td>[TAF]_2</td>
<td>D_2</td>
</tr>
<tr>
<td>:</td>
<td>:</td>
</tr>
<tr>
<td>[TAF]_N</td>
<td>D_N</td>
</tr>
</tbody>
</table>

Ascending Order

<table>
<thead>
<tr>
<th>[TAF]_[1]</th>
<th>D_[1]</th>
</tr>
</thead>
<tbody>
<tr>
<td>[TAF]_[2]</td>
<td>D_[2]</td>
</tr>
<tr>
<td>:</td>
<td>:</td>
</tr>
<tr>
<td>[TAF]_[N]</td>
<td>D_[N]</td>
</tr>
</tbody>
</table>
4. Dynamic Time Warping Scenarios (3/3)

<table>
<thead>
<tr>
<th>[TAF]_1</th>
<th>D_1</th>
</tr>
</thead>
<tbody>
<tr>
<td>[TAF]_2</td>
<td>D_2</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>[TAF]_N</td>
<td>D_N</td>
</tr>
</tbody>
</table>

The number of scenarios:

\[
n = \arg \max_k \frac{1}{\sum_{j=1}^{k} \frac{1}{(D_{[j]})^{DF}}} \geq P_{min}
\]
###WF = 1, Minimum cost path = 3.304

<table>
<thead>
<tr>
<th>period</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>0.030</td>
<td>0.254</td>
<td>0.071</td>
<td>0.200</td>
<td>0.084</td>
<td>0.109</td>
<td>0.476</td>
<td>0.549</td>
<td>0.041</td>
<td>0.632</td>
</tr>
<tr>
<td>9</td>
<td>0.267</td>
<td>0.113</td>
<td>0.276</td>
<td>0.146</td>
<td>0.164</td>
<td>0.098</td>
<td>0.781</td>
<td>0.522</td>
<td>0.188</td>
<td>0.824</td>
</tr>
<tr>
<td>8</td>
<td>0.578</td>
<td>0.089</td>
<td>0.516</td>
<td>0.268</td>
<td>0.341</td>
<td>0.301</td>
<td>1.007</td>
<td>0.500</td>
<td>0.473</td>
<td>0.914</td>
</tr>
<tr>
<td>7</td>
<td>0.105</td>
<td>0.650</td>
<td>0.212</td>
<td>0.520</td>
<td>0.403</td>
<td>0.137</td>
<td>1.030</td>
<td>1.273</td>
<td>0.086</td>
<td>1.332</td>
</tr>
<tr>
<td>6</td>
<td>0.077</td>
<td>0.285</td>
<td>0.009</td>
<td>0.436</td>
<td>0.199</td>
<td>0.334</td>
<td>0.377</td>
<td>0.519</td>
<td>0.184</td>
<td>0.454</td>
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###WF = 10, Minimum cost path = 3.748

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Three variables

- Weighing Factor (WF)
- Dimension Factor (DF)
- Minimum Probability ($P_{\text{min}}$)

A higher value of DF would penalize the days which are less similar to the day-of-operation.

$DF = 0$ implies that weather forecasts are not useful in decision making.
Three variables

Weighing Factor (WF)

Dimension Factor (DF)

Minimum Probability ($P_{\text{min}}$)

A lower value of $P_{\text{min}}$ increases the number of scenarios

$$n = \arg\max_k \frac{1}{\sum_{j=1}^{k} \frac{1}{(D_{[j]})^{DF}}} \geq P_{\text{min}}$$
Step 2: Balancing local and global searches (Regis & Shoemaker, 2007)

At iteration \( n \); Previously evaluated points: \( x_1, x_2, \ldots, x_n \)

Estimate a response surface using all the historical points: \( \hat{s}_n \)

Determine \( \hat{s}_n^{\text{max}} = \max_x \hat{s}_n(x) \) and \( \hat{s}_n^{\text{min}} = \min_x \hat{s}_n(x) \)

Define \( V_n^R(x) = (\hat{s}(x) - \hat{s}_n^{\text{min}})/(\hat{s}_n^{\text{max}} - \hat{s}_n^{\text{min}}) \)

Determine \( \Delta_n(x) = \min_j \|x - x_j\|^2 \) and \( \Delta_n^{\text{max}} = \max(\Delta_n(x)) \), \( \Delta_n^{\text{min}} = \min(\Delta_n(x)) \)

Define \( V_n^D(x) = (\Delta_n^{\text{max}} - \Delta_n(x))/(\Delta_n^{\text{max}} - \Delta_n^{\text{min}}) \)

Define a metric \( W(x) = w_n^R V_n^R + w_n^D V_n^D, w_n^R + w_n^D = 1 \)

\( x_{n+1} = \min_x W(x) \)

A higher \( w_n^R \) promotes local search and a smaller value promotes global search
3. Scenarios from Stratus forecast

- Binned days according to their burn off time
- Scenarios: Average of the realized AAR profiles in a bin
- Probabilities: From the STRATUS forecast

<table>
<thead>
<tr>
<th>Date</th>
<th>Fcst</th>
<th>Pr10</th>
<th>Pr11</th>
<th>Pr12</th>
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<tbody>
<tr>
<td>6/17/2004</td>
<td>11:31</td>
<td>5%</td>
<td>30%</td>
<td>65%</td>
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</table>

\[ P(\text{Burn off} < 10) = P_{10}, \]
\[ P(\text{Burn off} < 11) = P_{11}, \]
\[ P(\text{Burn off} < 12) = P_{12}. \]

Linear interpolation to construct the CDF (fog burns off completely by end of the day)

Probability of a Bin, \( b \), is then

\[ P_b = \Pr(\text{Burnoff} \leq \left\lfloor b \right\rfloor) - \Pr(\text{Burnoff} \leq \left\lfloor b \right\rfloor) \]

\[ P_{9:30-9:45} = \Pr(\text{Burnoff} \leq 9:45) - \Pr(\text{Burnoff} \leq 9:30) \]
Prob. capacity scenario : Methodology

Scenarios are the average realized capacity
Probability from day of the operation STRATUS forecast
Prob. capacity scenario : Methodology

Terminal Aerodrome Forecast (TAF)

- Date and Time of issue (1st and 1121Z)
- Wind direction and speed (280°, 6Knots)
- Sky conditions (clouds and their height in 100s of feet; scattered at 20,000 feet)
- Visibility (6 Statute Miles)

- Airport Code
  - KSFO 01121Z 011212 28006KT P6SM FEW010
  - TEMPO 1316 BKN010
    - FM1800 29010KT P6SM SCT200
    - FM2200 27018KT P6SM SCT200
    - FM0400 27010KT P6SM SKC

- Temporary forecast for 13Z-16Z
- Forecast for 24+4Z

- Forecast 7 metrological variables
- Forecasts conditions up to 24 hours in the future
- Forecast issued for all major US airports
- Each days TAF can be represented by 420 variables (7 variables * 60 time periods)
4. TAF Clustering

$[TAF]_{420 \times N}$ Matrix = $[TAF_1, TAF_2, \ldots, TAF_N]$

**Principal Component Analysis**
Dimension reduction tool.
Represents the variability in data in a smaller number of variables.
Reduces 420 variables to 10 PC variables (90% variability)

**Kmeans Clustering**

TAF Cluster 1  TAF Cluster 2

**Kmeans Clustering**

AAR

AAR Cluster 1,1  AAR Cluster 1,2
AAR Scenario 1,1  AAR Scenario 1,2

AAR Cluster 2,1  AAR Cluster 2,2
AAR Cluster 2,3
AAR Scenario 2,1  AAR Scenario 2,2  AAR Scenario 2,3
A day of operation is classified according to its TAF in either one the clusters. Depending on the classification, it’ll have either 2 or 3 scenarios.
Step 2: Balancing local and global searches (Regis & Shoemaker, 2007)

An ideal candidate point
1) Have a low estimated function value (since the goal is to minimize)

2) Should be far away from previously evaluated points (since this promotes a more global search).
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When the algorithm terminates, it provides the lowest average total delay costs and the values of the three variables. It determines values for WF, DF and Pmin which minimize the average total delay costs.
En route scenarios: Ensemble forecast

28 Ensemble Members
For Each Model Run