Probabilistic Runway and Capacity Forecasting using Machine Learning to Support Decision Making

SESAR Innovation Days 2016 – November 9, Delft
- Probability forecast of runway use and runway capacity
- Prototype in use at KLM’s Operations Control Centre (OCC) at Schiphol Airport
Schiphol Situation

Runway Use at Schiphol
- 6 runways
- Used in 80+ different runway combinations
- Alternates between departure and arrival peaks
- Configuration changes at least 14x per day

Runway selection
- Weather conditions
- Demand
- Noise preferential system
- Runway availability

Schiphol alternates between departure and arrival peaks
Motivation

Factors affecting airline performance

- Runway Capacity
  - On-time performance
  - Airborne holding
- Runway Use
  - On-time performance
  - Taxi-time

Timely actions required when performance at risk

- Possible actions include:
  - Re-route passengers
  - Take extra fuel on board
- Flight preparation starts up to 20-24 hrs in advance
- Decisions based on forecasts

Probabilistic Forecast

- Uncertainty of meteorological forecast
- Runway selection under influence of factors that cannot easily be captured or modelled
• Developed together with KLM OCC
• 30 hour probabilistic forecast
- Overview of the next 30 hours
- Capacity vs. Demand per 20 minute period
- Capacity available with a probability of 50% or more
- 20 minute period clickable to get more detailed information
For the selected 20 minute period
- Runway combinations, probabilities, capacity
- What-if scenarios
  - Different runway mode (e.g. outbound peak instead of inbound peak)
  - Visibility conditions (e.g., marginal instead of good)
Capacity table
- Same information as graph
- Summary of meteo

Meteo for 20 minute period
- Most likely
- Uncertainties
Probabilistic Forecast

Probabilistic Meteorological Forecast × Probabilistic Runway Use Forecast

“probabilistic meteo forecast x probabilistic runway use forecast”
- Run Monte Carlo simulations with the runway use model
- Vary meteorological conditions based on meteo forecast
- Aggregate simulation results to obtain the probability forecast
## KNMI PROBABILITY FORECAST SCHIPHOL

**Friday 21 November 12 UTC till Saturday 22 November 18 UTC**

*Last update: Short term: 09:45 UTC  Long term: 10:57 UTC*

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*Source: KNMI*

- Product of the Royal Netherlands Meteorological Institute (KNMI)
- Probability forecast up to 30 hours
- Updated every hour
Probability Forecast Runway Use

- 1 Landing +1 Take-off
- Wind 310° 10 kts
- Good visibility, in UDP

Runway combination and probability:

<table>
<thead>
<tr>
<th>Runway Combination</th>
<th>Probability</th>
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<tbody>
<tr>
<td>36L/06</td>
<td>60%</td>
</tr>
<tr>
<td>36L/36R</td>
<td>30%</td>
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<tr>
<td>36L/27</td>
<td>10%</td>
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</tbody>
</table>

Model Predictors

- Available runways
- Number of departure and arrival runways needed
- Wind direction, wind speed and gust
- Visibility (horizontal & cloud base)
- Daylight conditions (yes/no)
Supervised Machine Learning

- The computer is presented with example inputs and their desired outputs, given by a ‘teacher’, and the goal is to learn a general rule that maps inputs to outputs.

1 – Training phase

2 – Prediction phase

Multinomial Logistic Regression

- Predicts the probabilities of all possible runway combinations
- The runway combination is considered a nominal dependent variable
  - the number of categories is limited (i.e., 82 unique runway combinations),
  - there is no ordering in any meaningful order
  - all categories are known
Machine Learning Runway Use Model

Training phase (prior to use)

<table>
<thead>
<tr>
<th>Weather</th>
<th>Runway Use</th>
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<tbody>
<tr>
<td>Wind</td>
<td>Visibility (GMB)</td>
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<tr>
<td>320 10kt</td>
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<td>320 10kt</td>
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<td>310 10kt</td>
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<td>310 10kt</td>
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<td>310 10kt</td>
<td>G</td>
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<tr>
<td>180 6kt</td>
<td>M</td>
</tr>
</tbody>
</table>

Prediction phase (use)

give runway combinations and probability for the following conditions:
- 1 dep runway and 1 arr runway
- Wind 310 10 kts
- good visibility, within UDP

Model

combination | prob. |
-------------|-------|
36L/06       | 60%   |
36L/36R      | 30%   |
36L/27       | 10%   |
Monte Carlo simulations with runway use model

20 minute period

select peak periods

draw meteo condition

departure arrival, peak etc.

meteo-condition

runway use model

prob. forecast runway use for 1 meteo condition

aggregate results individual simulations

probability forecast runway use

“probability forecast meteo x probability forecast runway use”

- Series of Monte Carlo simulations with runway use model
- Varying meteorological conditions based on probabilistic forecast
- Runway model gives probabilistic forecast for one meteo condition
Predictive Power

- Reliability of the model
- “Confidence” of the model

- Trained model using 2013 data
- Generated probability forecasts for 2014
- Compared the forecast with actual runway use
Forecast vs. Actual Use – runway use model only

- Strong correlation between forecast and actual use
Forecast vs. Actual use against the prediction horizon
Impact on Decision Making

- User experiment
- Type of decision made
- Time a decision was made

- Use of the system
- Get feedback on the design and functionality
Impact on Decision Making

- KLM selected 5 days to assess the impact on decision making in an experiment
  - Storm, snow, showers, bad visibility

- Three participants
  - 2 x Supervisor Flight Dispatch
  - 1 x Flow Controller
  - No experience with the system

- Impact on decision making
  - Fuel advice (e.g., extra fuel for expected holding)
  - Inform ‘network operations’ (e.g. cancel flights)
  - Compare decisions taken during the experiment run and the actual operation
Experiment Setup

- Scenario starts at 7:00z the day before (D -1)

- The participant is asked to assess the situation using the DSS system. Also available to the participant are weather information and the latest briefing.

- The participant is asked to:
  1. Describe the situation
  2. Indicate which conclusions he/she draws based on the information
  3. Indicate if operational decisions should be taken.
     If yes, indicate which operational decisions.

- The steps above are repeated at 15:00z (D -1), 23:00z (D -1), 7:00z (D 0) at the day itself.

- Same steps as in the actual operation
Comparison of Decisions Taken

- No impact on the ‘type’ of operational decisions that are made
  - Fuel advices more targeted to fleet segments (EUR/ICA) and time frame

- Possible effect on the moment decisions are made
  - Fuel advices later
  - Cancellations earlier

- Sample size is too small to draw any statistical significant conclusions
User Feedback & Interface Use (selection)

- The capacity graph works as a trigger. When demand exceeds capacity, users explore the situation further.

- The system enables more targeted decision making.

- More focus on the middle of the day.

- Capacity table adds little information, can be removed.

- Difficult to see how the weather is changes over time, requires many mouse clicks.

- Crosswind per runway and capacity penalty due to headwind would be a valuable addition.
Main Conclusions

- Combining the probabilistic runway use forecast with a probabilistic meteorological forecast results in a probabilistic forecast that accounts for both the uncertainty in the weather forecast and runway selection.

- Probabilities forecast have strong correlation with the percentage of time a runway is actually used.

- Indication that the system has a positive effect on decision making
  - decisions to cancel flights are taken earlier.
  - decisions to take extra fuel onboard later.
  - more targeted decision making
This project was funded by
Probabilistic Runway and Capacity Forecasting using Machine Learning to Support Decision Making

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