Prediction of passenger boarding progress using neural network approach

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Outline

• Background

• Boarding model

• Long short-term memory model

• Results

• Outlook
**Background**

*aerial trajectory, ground operations, boarding*

- International Civil Aviation Organization (ICAO), Aviation System Block Upgrades (ASBU) → Timeline to implement efficient flight paths

- Trajectory Based Operations (TBO)
  - Global ATM Operational Concept (Doc. 9854)
  - Flight & Flow Information for a Collaborative Environment (Doc. 9965)
  - Need for a System Wide Information Management (SWIM, Doc. 10039)

- Aircraft trajectory – not only flight path
  - Milestone concept available - A-CDM
  - 4D ground trajectory – including ground operations (turnaround)
  - Critical path
    - 70€ per delay minute
    - Boarding is always on critical path (particularly important for flights with high number of rotations, short haul)
**Background**

*aerospace trajectory, ground operations, boarding*

**Variability on intra-European flights (2008-2015)**

- **Range (80th-20th percentile)**
- **Standard deviation**

*Variability on intra-European flights (2008-2015)*

- **Departure time**
- **Taxi-out phase**
- **Flight phase**
- **Taxi-in phase**
- **Arrival time**

*Eurocontrol, CODA*
Background

*aerospace trajectory, ground operations, boarding*

![Diagram showing various ground operations and delays](chart5.png)

- **Boarding**
- **Fueling**
- **Catering**
- **Cleaning**
- **Deboarding**

**Legend:**
- Black: delay between 25-30 min
- Gray: delay between 10-15 min
- White: no delay (-5 min)

**On Block Time:** 10, 20, 30, 40, 50, 60

**Time (min):**

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*H. Fricke, M. Schultz. Delay impacts onto turnaround performance. ATM Seminar, 2009*
Ready for boarding

BOARDING ALL ROWS!

Rows 15 and higher. On your marks...get set...

BACK! BACK! Rows twenty and higher only!
Data-based vs. model-based approaches

*input data, models, new concepts*

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M. Schultz, *Field Trial Measurements to Validate a Stochastic Aircraft Boarding Model*, Aerospace 2018, 5(1), 27

Aircraft boarding
stochastic, individual-based model

Model - A320, 29 rows, 174 seats

- grid-based, stochastic processes (ASEP), fast implementation
- Operational aspects, e.g. seat load, arrival rates, boarding strategy
- Individual passenger behaviour, e.g. speed
Aircraft boarding
*stochastic, individual-based model*

Reliable simulation environment

Boarding pattern

Results compared to RANDOM boarding*
- average boarding time 0 % slower
- boarding time variation 0 % higher

*100k simulation runs*
Implementation

boarding strategies and operational constraints
**Problem to solve**

*boarding is owned by the passenger*

Different kind of **seat occupation** pattern demands for a specific amount of individual movements

Distribution and amount of hand **luggage pieces** results in blocked aisle when storing into the overhead compartment

**Pax could disturb** the whole boarding progress (connection flights, pax handling in terminal - security)

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**Distribution and amount of hand luggage pieces**

- **Triangular distribution (old model)**
- **Weibull distribution**
- **Field measurement**

**Probability (%)**

- **Arrival (pax per minute)**
  - **Scenario A (fast)**
  - **Scenario B (medium)**
  - **Scenario C (slow)**

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M. Schultz, *Field Trial Measurements to Validate a Stochastic Aircraft Boarding Model*, Aerospace 2018, 5(1), 27
How to predict passenger-controlled process?

boarding progress

Evaluation of seat status

complexity metric

- System state of seat rows and cabin
  (using future cabin management system and sensors)

Complexity metric

progress prediction
Machine learning approach

*artificial neural networks*

- Artificial Neural Networks (ANN) are characterized by interconnected neurons.
- Neurons structured in different layers, connection depends on computed weights, result in blocking or passing of information.
Machine learning approach

*recurrent neural network*

- Training neural networks demands for error estimation (backpropagation)

![Diagram of recurrent neural network](chart.png)
Machine learning approach

**short-term memory**

- Information to be passed from one step of the network to the next

- Long-term dependency problem (need for more context)
Machine learning approach

*long short-term memory (LSTM)*

- Repeating module in a RNN and LSTM

http://colah.github.io/posts/2015-08-Understanding-LSTMs/
Machine learning approach

**LSTM implementation**

- Implementation in Python 3.6, TensorFlow (backend), Keras (frontend)
- Basic model: core layers (Dense, Dropout), recurrent layers (LSTM)
- Boarding model: concatenation of 1 - 3 separate LSTM branches
Machine learning approach

LSTM implementation
Input data – complexity measures

boarding simulation to train and evaluate

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Prediction of boarding progress

- fast boarding - original seat load
- slow boarding - original seat load
- fast boarding - predicted seat load
- slow boarding - predicted seat load
Outlook

handle input data - smooth
Thank you.

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References


S. Reitmann and M. Schultz, Advanced Recurrent Neural Network based Aircraft Boarding Prediction. ATRS conference 2018