TECHNISCHE UNIVERSITÄT
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An Adaptive Framework for Optimization and Prediction of Air Traffic Management (Sub-)Systems with Machine Learning

Applied Machine Learning Days

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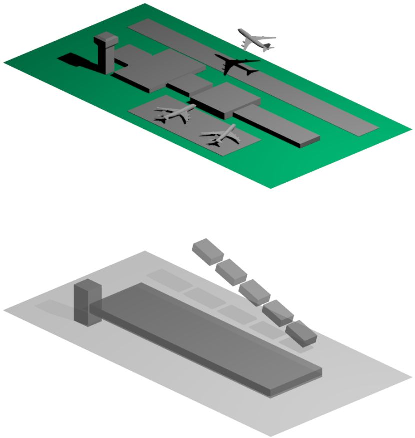
CONTENT



PERFORMANCE BASED AIRPORT MANAGEMENT

- Stakeholders: airport, airline, air traffic control, ground traffic
- Performance-based concepts serve for operational coordination

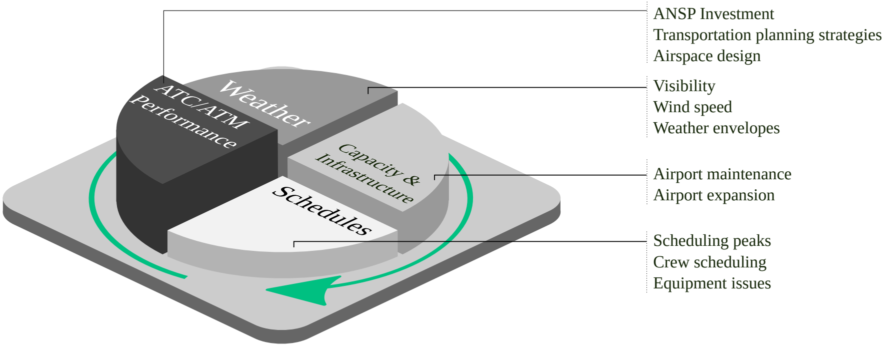


Abb. 1: Interdependencies in the operational management of an air traffic system.

PERFORMANCE BASED AIRPORT MANAGEMENT

- Different concepts for the optimization of airport processes considering all involved stakeholders (A-CDM, TAM, PBAM)

Nr.	Milestone	Nr.	Milestone
1	ATC Flight Plan activation	9	TOBT update prior to TSAT
2	EOBT - 2hr	10	TSAT issue
3	Take off from outstation	11	**Boarding starts**
4	Local radar update	12	**AC ready**
5	Final approach	13	tart up request
6	Landing	14	Start up approved
7	**In-block**	15	**Off-block**
8	Ground handling starts	16	Take off

Tab. 1: Milestones of Airport-Collaborative Descision Making (A-CDM).

PERFORMANCE BASED AIRPORT MANAGEMENT

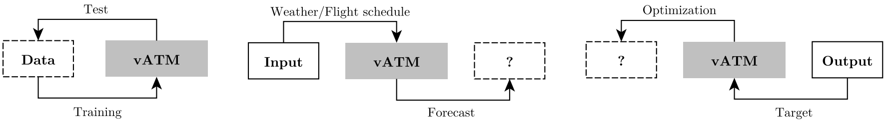


Abb. 2: Components of the virtual ATM system (*vATM*): system identification (left), simulation (middle), control (right).

Flight schedule/weather	vATM	Delay	Description
given	**unknown**	given	*System identification*
given	given	**unknown**	*Simulation*
unknown	given	given	*Control*

Tab. 2: Input and output define the vATM process.

APPLICATIONS

Boarding as part of turnaround of an Airbus A320-300

Data:	stochastic boarding simulation
Data scope:	150.000 simulations of 6 strategies
Metric/Features:	complexity metric, 4 features

ATFM scenarios for Hamburg (HAM) and London Gatwick (LGW)

Data:	performance and weather data 2012-2015
Data scope:	12.762 flights (HAM) and 63.854 flights (LGW)
Metric/Features:	12 ATFM KPIs, 6 / 12 weather features

DATA AGGREGATION - WEATHER

METAR: Meteorological Aerodrome Report, historical
TAF: Terminal Aerodrome Forecast, forecast (6h)
ATMAP: Air Traffic Management Airport Performance, weather classes

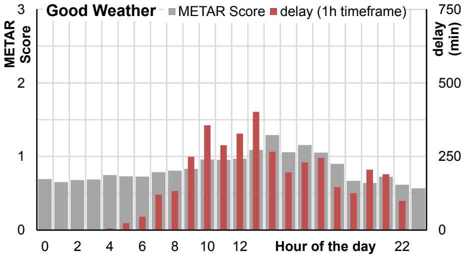


Abb. 3: HAM, good weather (ATMAP).

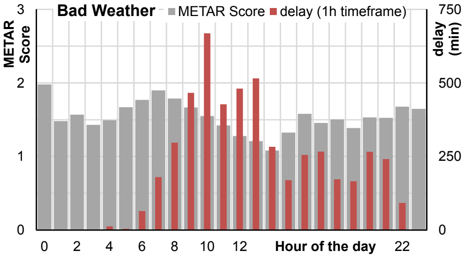


Abb. 4: HAM, good weather (ATMAP).

SYSTEM IDENTIFICATION

Modular framework for applications of ANN in PBAM concepts [1]

Problem identification:	system selection, problem definition, data aggregation
Data structure analysis:	preparatory actions & customizations ▪ exploratory data pre-analysis ▪ data preprocessing (cleaning, adaptation) ▪ ML adaptation (feature selection, data split)
Model configuration:	paradigm selection, output definition
Model application:	model initialization, traininig, validation, visualization
Downstream analysis:	optimization, stability

SYSTEM IDENTIFICATION - PROBLEM IDENTIFICATION

Aircraft boarding as part of the turnaround of an Airbus A320-300

Scenario A: random - random

Scenario B: individual - individual

Scenario C: random - individual

ATFM analysis for Hamburg (HAM) and London Gatwick (LGW)

Scenario A: without restrictions

Scenario B: weather restrictions (good, bad)

Scenario C: weather restrictions, similar demand

SYSTEM IDENTIFICATION - DATA STRUCTURE ANALYSIS

HAM: Capacity 48 flights/h, 2 RWYs (crossed)
LGW: Capacity 55 flights/h, 1 RWY

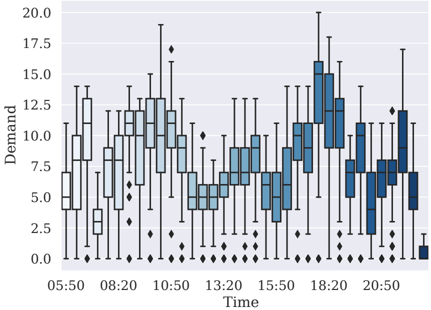


Abb. 5: HAM, demand.

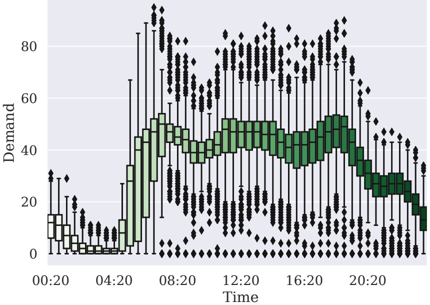


Abb. 6: LGW, demand.

SYSTEM IDENTIFICATION - LABELING

- Base class of Eurocontrol: [-5,15] minutes = on time.
- Labling of the data based on the base class and distributions.

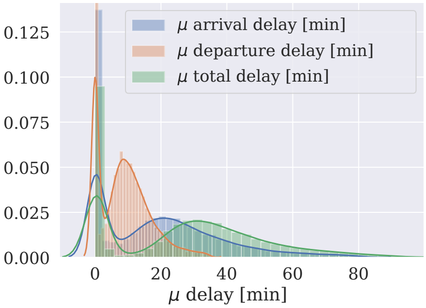


Abb. 7: LGW, delay distribution.

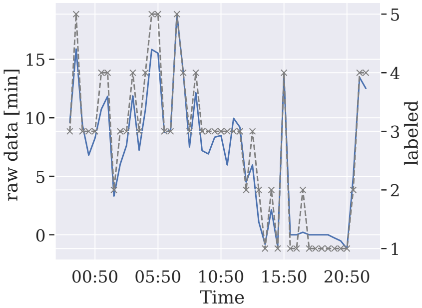


Abb. 8: LGW, labeling of raw data to reduce dimensions.

SYSTEM IDENTIFICATION - DATA SPLIT

- Flight demand is decisive attraction of vATM
- use of *Dynamic Time Warping* for detection of similar days

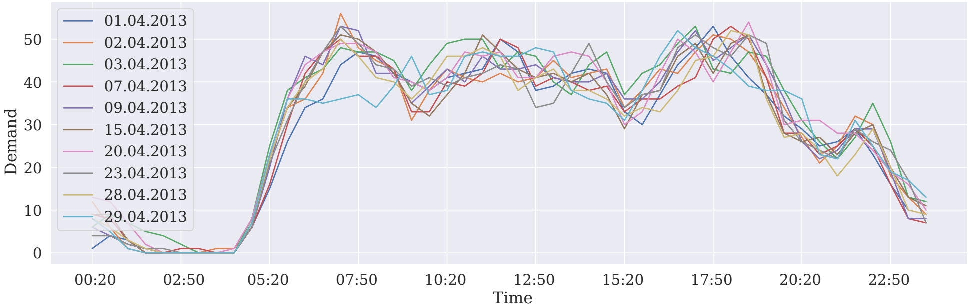


Abb. 9: LGW, application of DTW to detect 10 days with similar demand in Apr 2013.

SYSTEM IDENTIFICATION - FEATURE CHOICE

- operational features are given (Demand, n_{ARR}, n_{DEP}).
- *Recursive Feature Elimination* (supervised) + *Variance Threshold* (unsupervised) to select weather features. [12]

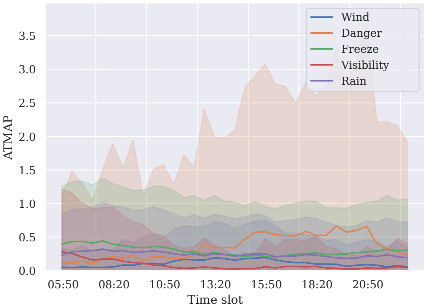


Abb. 10: HAM, feature variations.

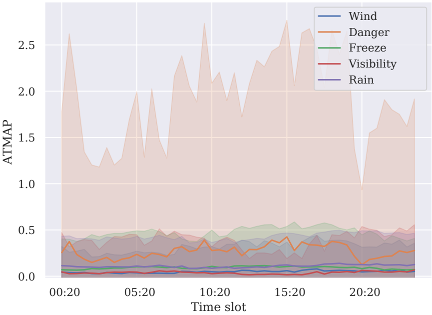


Abb. 11: LGW, feature variations.

SYSTEM IDENTIFICATION - MODEL APPLICATION

- Determination of the hyperparameters of the neural networks via *Grid Search*
- empirical values from comparable experiments and derived rules from literature define the grid search intervals

Tab. 3: Structure of ANN (left) and hyperparameter for grid search (right) of ATFM classification [5].

	LSTM	Conv1D	ConvLSTM2D	Dropout	MaxPooling1D	Flatten	Dense
LSTM	x			x			x
CNN		x		x	x	x	x
CNN-LSTM	x	x		x	x	x	x
ConvLSTM			x	x		x	x

Hyperparameter	Value range
Batch	[20,40,60,80,100]
n_{epochs}	[10,100]
Optimizer	[AdaDelta, RMSprop, Adam]
Learning rate η	[0.001, 0.01, 0.1]
Momentum ϱ	[0.0, 0.2, 0.4, 0.6, 0.8, 0.9]
U_{hidden}	[10, 100, 500, 1000]
Dropout rate	[0.0, 0.2, 0.4, 0.6, 0.8, 0.9]

SYSTEM IDENTIFICATION - TRAINING

- strong constraint on boarding data required
- estimation of n_{epochs} supported by learning curves

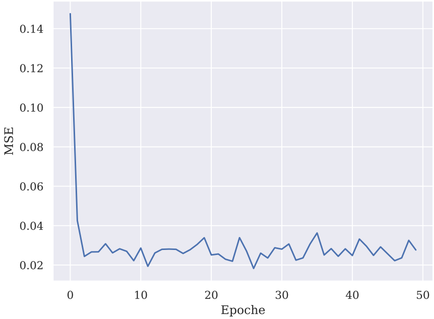


Abb. 12: Boarding, MSE.

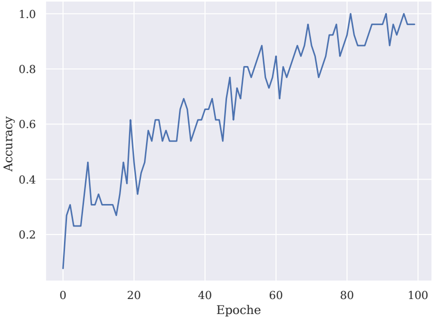


Abb. 13: LGW, accuracy of classification.

SIMULATION / FORECAST - ATFM

- Specifications of the data sets improve the results
- For arrivals (ARR) no usable prediction model is achievable
  - Reshape the problem to a predictive classfication.
  - Improvement of prediction for multiclasses (58.8%) and binary classes (72.1%) with a 12-step prediction [3]

Tab. 4: Results of calculations for scenarios A (no constraints) and B2 (bad weather) from prediction start 11:20. All values are in [min] [12, 5].

Scenario	$\widetilde{\Xi}$ *(total)*	$\widetilde{\Xi}$ *(single)*	$\widetilde{\Xi}$ *(single)*
A	[ARR + DEP]	[ARR]	[DEP]
HAM	8.50	5.23	5.49
LGW	27.86	17.85	8.37
B2	[ARR + DEP]	[ARR]	[DEP]
HAM	9.91	5.41	3.39
LGW	27.14	20.93	6.95

CONTROL/OPTIMIZATION - ROBUSTNESS

- Synthetically generation and feeding of *Adversarial Examples*
- Simulation of measurement errors (boarding) and capacity extremes (ATFM)

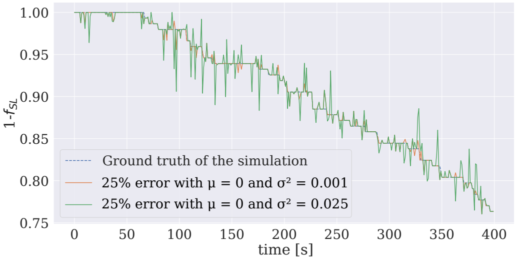


Abb. 14: Boarding, simulation of measurement errors.

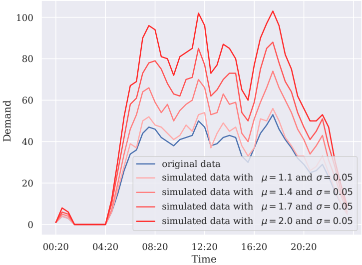


Abb. 15: LGW, simulation of capacity extrema.

CONTROL/OPTIMIZATION - EXTRACTION

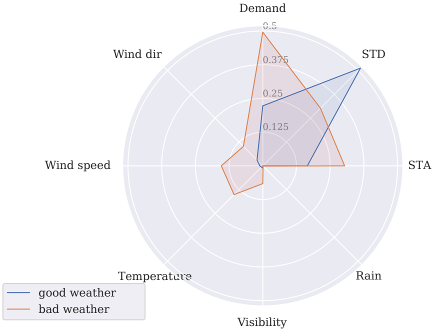


Abb. 16: LGW, features importance for departing flights.

- Goal: Feature influence extraction
- Feed-forward networks allow direct extraction from parameters
- Recurrent networks have to be treated as black box models
- Use of *Permutation Importance*

CONTROL/OPTIMIZATION - METAHEURISTICS

- recurrent structures $\rightarrow$ metaheuristic optimization methods
- use of nature-analog *Particle Swarm Optimization (PSO)*

$$\begin{aligned} &\text{min} \quad \frac{1}{n}\sum_{t=1}^{n} \text{kNN}(t) && n = 12 \\ &\text{with} \quad \text{Demand}(t) = \text{STD}(t) + \text{STA}(t) && \forall t \in \Gamma_{opt} \end{aligned}$$

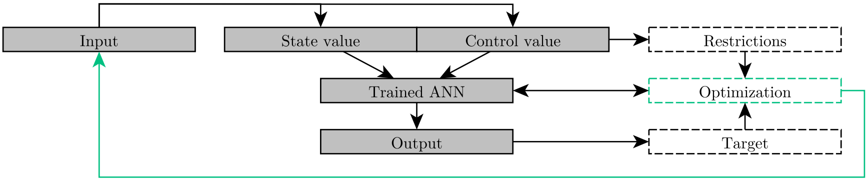


Abb. 17: Schematic representation of a (global) PSO with restrictors.

3. CONTROL/OPTIMIZATION - METAHEURISTICS

Tab. 5: PSO results (example) of calculations for LGW on May 01 2015.

Original	$t+1h$	$t+2h$	$t+3h$	$t+4h$	$t+5h$	$t+6h$	$\sum$	μ Delay
Demand$_{\text{original}}$	48	48	51	41	27	26	494	13.44 min
Demand$_{\text{PSO}}$	54	47	54	43	28	29	499	10.09 min

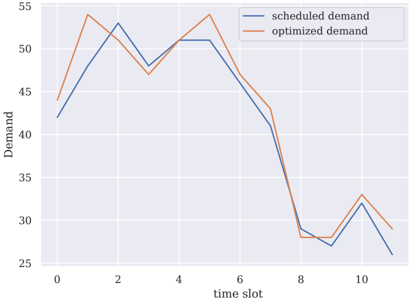


Abb. 18: Optimization with 10% variation.

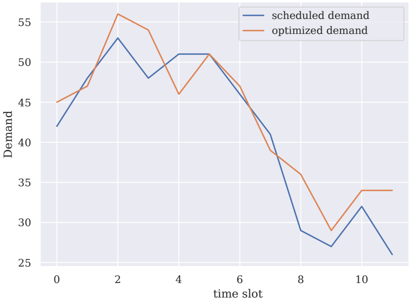


Abb. 19: Optimization with 25% variation.

CONCLUTION & OUTLOOK

- first-time data-driven prediction of aircraft boarding
- partially improved predictions in ATFM despite macroscopic data
- derivation of recommended actions and optimizations
  - → Application support for ANN in air traffic management
  - → Extension of existing performance-based concepts by ANN

- Expansion of data sets used (operational), especially with regard to capacity data
- Analysis within the airspace or network, not only locally
- Stability studies of the ANN

PUBLICATIONS

[1] Stefan Reitmann und Michael Schultz. “An Adaptive Framework for Optimization and Prediction of Air Traffic Management (Sub-)Systems with Machine Learning”. In: *Aerospace* 9.2 (2022). ISSN: 2226-4310. DOI: 10.3390/aerospace9020077. URL: https://www.mdpi.com/2226-4310/9/2/77.

[2] Michael Schultz, Stefan Reitmann und Sameer Alam. “Predictive classification and understanding of weather impact on airport performance through machine learning”. In: *Transportation Research Part C: Emerging Technologies* 131 (2021), S. 103–119. ISSN: 0968-090X. DOI: 10.1016/j.trc.2021.103119. URL: https://www.sciencedirect.com/science/article/pii/S0968090X21001388.

[3] S. Reitmann, M. Schultz und S. Alam. “Advanced Quantification of Weather Impact on Air Traffic Management”. In: Air Traffic Management Research and Development Seminar (ATM2019). Wien, Österreich, Juni 2019.

[4] M. Schultz und S. Reitmann. “Machine learning approach to predict aircraft boarding”. In: *Transportation Research Part C: Emerging Technologies* 98 (Jan. 2019), S. 391–408. ISSN: 0968-090X. DOI: 10.1016/j.trc.2018.09.007. URL: http://www.sciencedirect.com/science/article/pii/S0968090X18312580.

[5] S. Reitmann und M. Schultz. “Computation of Air Traffic Flow Management Performance with Long Short-Term Memories Considering Weather Impact”. In: *Artificial Neural Networks and Machine Learning – ICANN 2018*. Bd. 11140. Lecture Notes in Computer Science. Springer, 2018, S. 532–541. ISBN: 978-3-030-01421-6. DOI: 10.1007/978-3-030-01421-6_51. URL: http://dx.doi.org/10.1007/978-3-030-01421-6_51.

[6] S. Reitmann und M. Schultz. “Real-Time Prediction of Aircraft Boarding”. In: Digital Avionics Systems Conference (DASC). London, UK, 2018.

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[8] M. Schultz und S. Reitmann. “Consideration of Passenger Interactions for the Prediction of Aircraft Boarding Time”. In: *Aerospace* 5.4 (Sep. 2018), S. 101. DOI: 10.3390/aerospace5040101. URL: https://www.mdpi.com/2226-4310/5/4/101.

[9] M. Schultz und S. Reitmann. “Prediction of Aircraft Boarding time Using LSTM network”. In: Winter Simulation Conference. Göteborg, Schweden, 2018.

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[11] S. Reitmann. “Ableitung eines mathematischen Wirkungsmodells durch systematische Analyse von Leistungsindikatoren”. In: Deutscher Luft- und Raumfahrtkongress (DLRK). München, Deutschland, 2017.

[12] S. Reitmann und K. Nachtigall. “Applying Bidirectional Long Short-Term Memories (BLSTM) to Performance Data in Air Traffic Management for System Identification.”. In: *ICANN (2)*. Hrsg. von Alessandra Lintas u. a. Bd. 10614. Lecture Notes in Computer Science. Springer, 2017, S. 528–536. ISBN: 978-3-319-68612-7. URL: https://doi.org/10.1007/978-3-319-68612-7_60.

[13] S. Reitmann und M. Schultz. “Stability Analysis of Recurrent Neural Networks for Time Series based System Control in Aviation”. In: International Science & Progress Conference. St. Petersburg, Russland, 2017.

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[14] S. Reitmann, A. Gillissen und M. Schultz. "Performance Benchmarking in Interdependent ATM Systems". In: International Conference on Research in Air Transportation (ICRAT). Philadelphia, USA, 2016.

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Thank you for your attention!