

Pre-Tactical Planning of Runway Utilization under Uncertainty: Optimization and Validation

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Overview

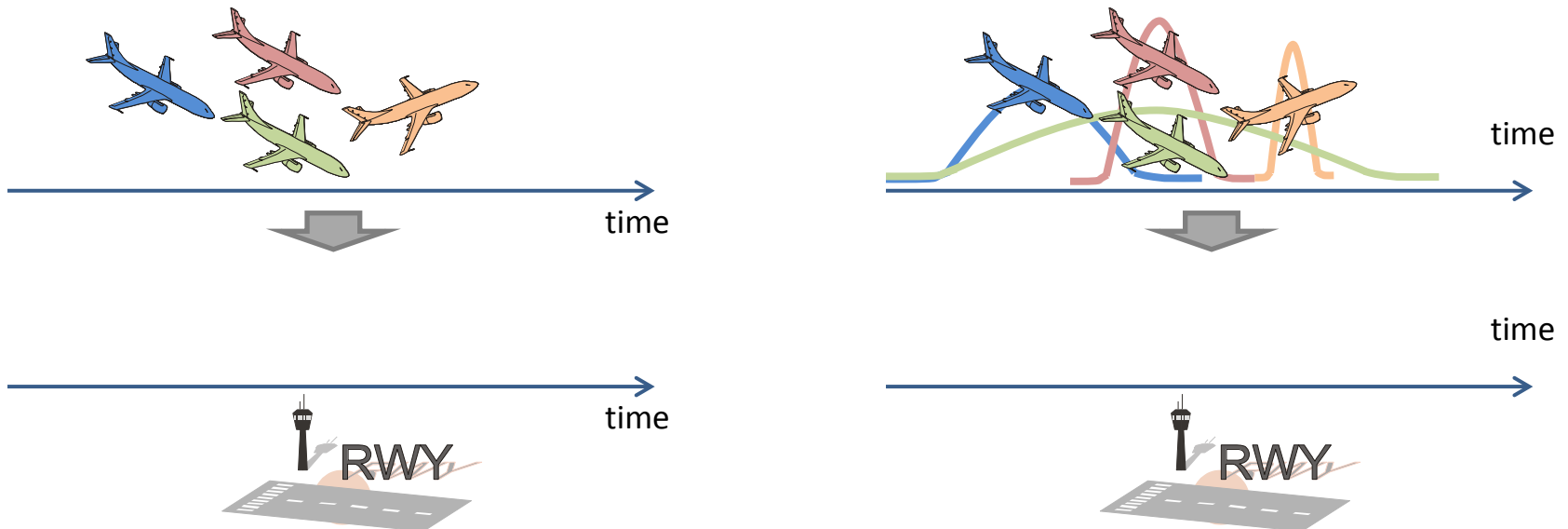
- **Introduction**
- Discrete Optimization under Uncertainty
- Empirical Delay Data & Disturbance Statistics
- Monte Carlo Computer Experiments & Discussion
- Conclusion



RobustATM Goal

Create **Optimized Robust Plans** for **Pre-Tactical Arrival Scheduling**
through **Consideration of Uncertainties**

First Come First Serve → Optimization under Uncertainty → Robust Planning / Less Re-Scheduling



New Optimization Models and Validation

- Design **new Optimization Models** with Protection against Random Disturbance for Robust Flight Plans through Statistical A-Priori Knowledge on Uncertainties

- **Validation through Monte-Carlo Simulation** with Random Disturbance of Plans
 - Scenarios: Scheduling using t-based trajectory & Random Departure Delay
 - Empirical data: Realistic Flight Plans with Stochastic Delay Models
 - Metrics: Quantifying new discrete optimization models
 - Define Baseline



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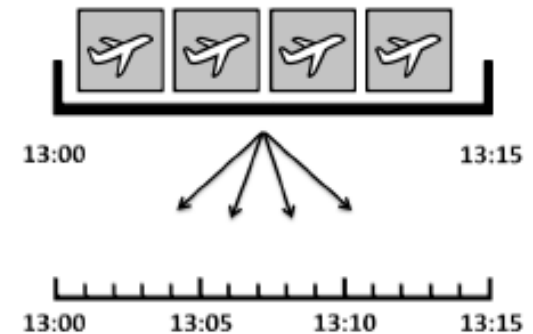


Mathematical Model: Discrete Time Window Assignment



~ 100 Time Windows / Day of Traffic

pre-tactical



tactical

How many Aircraft fit into one Time Window?

3 Weight Classes → Separation Matrix

A/C-Class Mix: 24 (12%) H, 14 (7%) L, 171 (82%) M

Minimum separation times (in seconds)

Pred. \ Succ.	Heavy	Medium	Light
Heavy	100	125	150
Medium	75	75	125
Light	75	75	75



Assignment Graph & Inclusion of Uncertainties

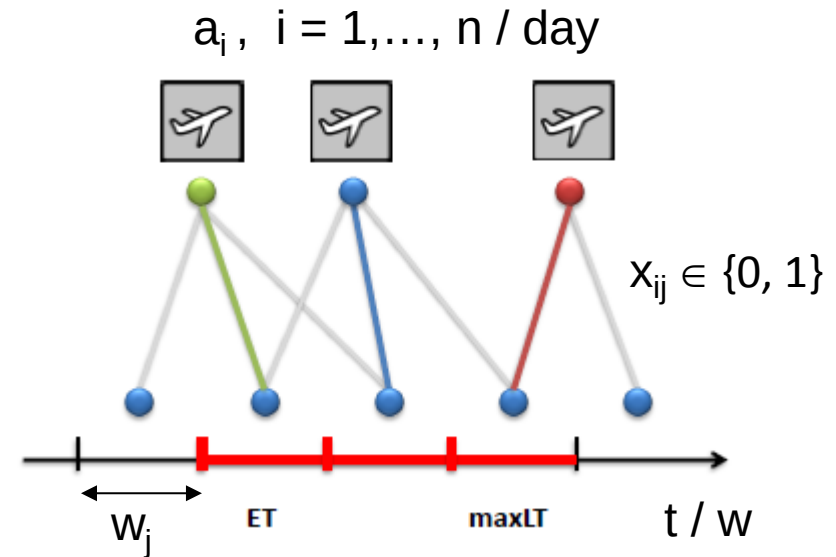
Assignment Decisions for Time-Window w_j

between Earliest / max Latest Arr.-Time:

Choose Edges Binary Variables $\rightarrow x_{ij} \in \{0,1\}$

$\rightarrow$ Set of Constraints $x_{ij}(LT(ET, TT, t^{Sim}))$

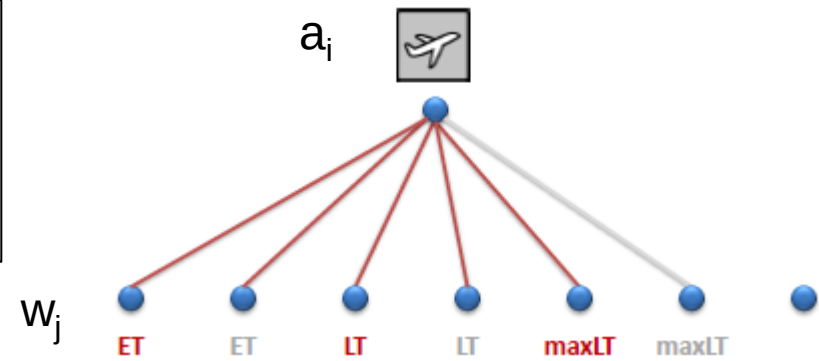
$\rightarrow$ Objective Function Penalizing Early (cost $\sim$ earliness) and Late Arrivals (cost $\sim$ delay²)



Random Disturbance: Each Realization k

Yields $[ET, LT(ET), Lt_{max}]_{ik}$

of Feasible Assignments $x_{ijk}(a_{ik} \rightarrow w_{jk})$



Protection against Unfeasible Assignments: Include A-Priori Knowledge on Uncertainties in Optimization Model (e.g. Dept. Delay-PDF(μ, σ))

1. Robust Model: Assignment Graph only contains edges that are feasible for every realization of Uncertainty Set (Disturbance-PDF(μ, σ)).

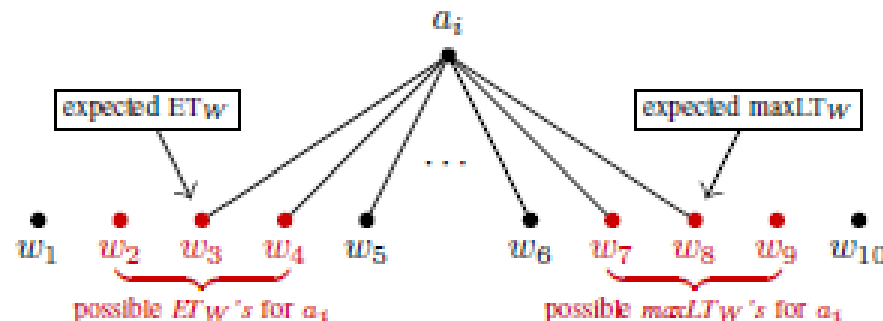
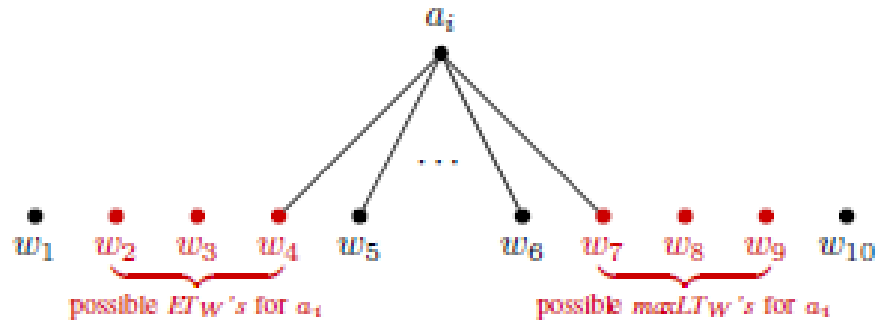
$$ET := ET + \mu + k \sigma, \quad k = 1, 2, \dots$$

$$LT_{MAX} := Lt_{max} + \mu - k \sigma,$$

2. Stochastic Model $k = 0$: Less Conservative.

Optimize over all assignments which are **expected** to be possible.

Only Shift by **Expectation** μ of Disturb.-PDF



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Analysis of Empirical Flight Data & Design of Stochastic Delay Model

Asymmetric Γ – PDF Model: delay-shift to $\mathbb{R}^+$ by max. Earliness: $t = \text{delay } t^D - t_{\min}^D$

$$f(t; \tau, a) = \left(\frac{a}{\tau}\right)^a \frac{t^{a-1}}{\Gamma(a)} e^{-\frac{at}{\tau}} \quad , t \geq 0$$

Shape Parameter a

$a = 1$: Poisson Process (max Randomness)

$a \rightarrow \infty : N(\mu, \sigma)$

Central Moments μ_i :

Mean $\mu_1 = \tau$

Stdev $\sqrt{\mu_2} = \sigma = \tau / \sqrt{a}$

Skewness $\gamma = \mu_3 / \sigma^3 = 2 / \sqrt{a}$

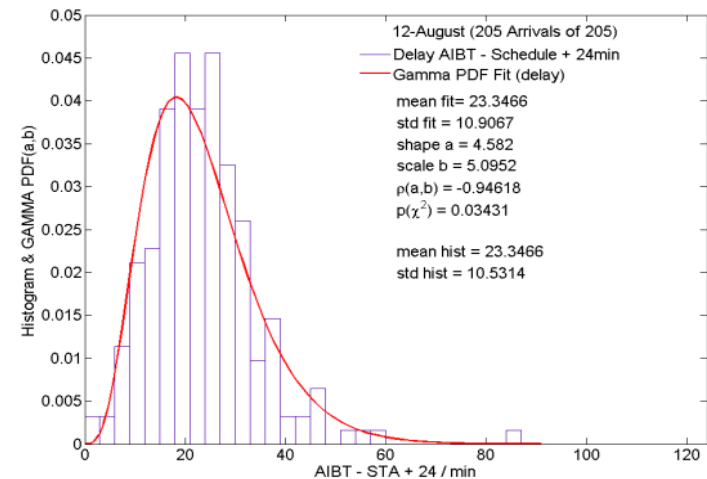


Empirical Arrival & Departure Delays from Int. German Airport

Example: Full Day (17 h) Arrival Delays

→ **Traffic Scenario 1:** 209 Flights / 17 hrs

→ **Traffic Scenario 2:** 209 Flights / 8 hrs

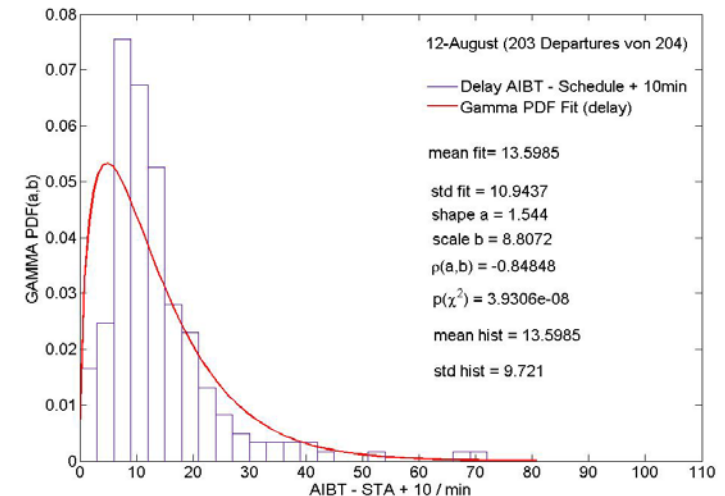


Example: Full Day Departure Delays

→ **Average Dept-Delay PDF (>150 Ldg. /Flight#):**

$\langle \mu \rangle = 7.3$ min, $\langle \sigma \rangle = 6.6$ min, $\langle a \rangle = 2.5$

Used for all Flights in MC-Simulations



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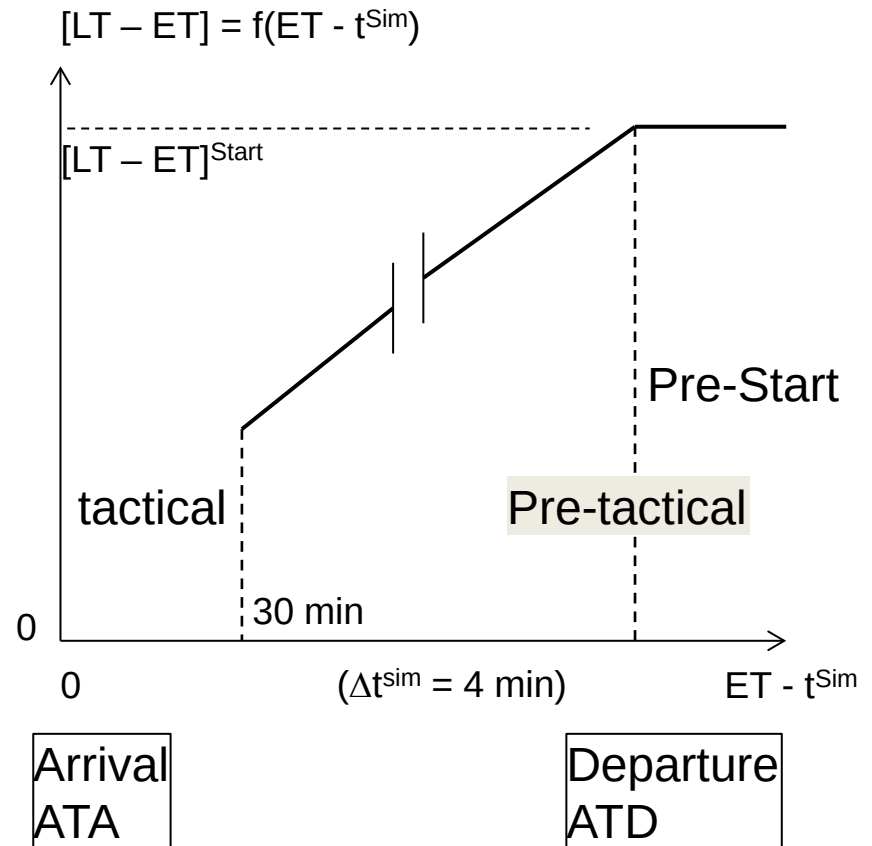
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Time Based Trajectory for MC-Simulation (pre-tactical, 30 min)

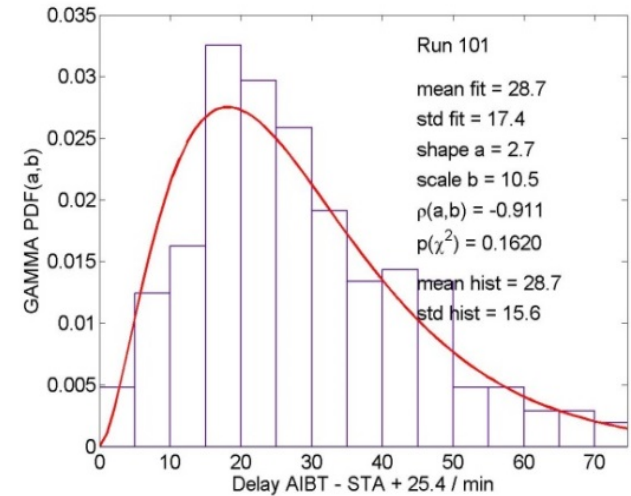
MC input data / a_i :

- Callsign(i), Weight-class(i),
- $ET_i < ST_i < LT_i < \max LT_i$
- Random delay $\langle \Gamma\text{-PDF}_i \rangle \rightarrow (TOT_i\text{-}STD_i)$

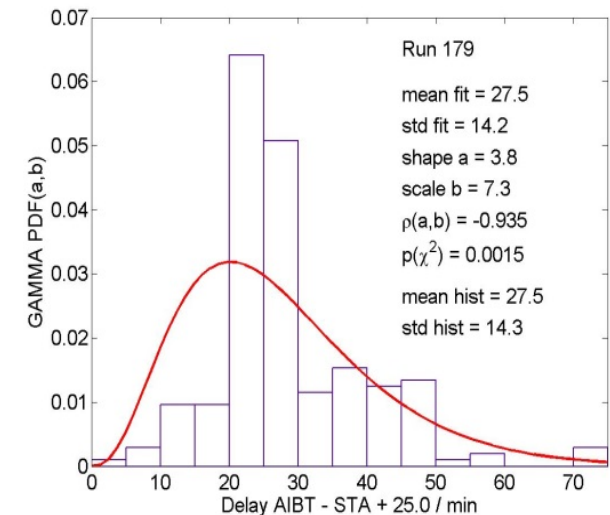


Examples: 1 Single Run from k = 1 ... 200 (Dense Traffic Scenario)

Baseline, no optimization FCFS (209 A/C / 8 h)



MIP-Gurobi Optimization FAU-Nominal (209 A/C / 8 h)



Comparison of new FAU-Models with Baseline: Dense Traffic

200 Runs (Days)
Averages

Baseline

New Models

Model (MC#)	Runtime ($\pm$ std) / sec	Shape Parameter a	Delay μ ($\pm$ std) / min	Re-Schedulings rs# ($\pm$ std)
FCFS (057)	1.1 (0.4)	2.5	5.3 (5.0)	12.7 (5.6)
TS8-2 (56)	203 (63)	3.5	3.5 (6.0)	8.1 (3.2)
FAU-N (87)	15.8 (1.5)	3.2	1.7 (3.9)	0.45 (0.27)
FAU-S (88)	16.7 (1.1)	0.9	3.0 (5.1)	0.38 (0.23)
FAU-R (89)	18.2 (1.2)	0.3	12.2 (0.6)	0.22 (0.26)



Conclusion

- New discrete optimization models with short runtime for pre-tactical scheduling developed, with protection against random disturbance
- Models successfully validated by means of MC-Simulations (significantly reduced rs#) using empirical flight schedules and random departure delays modeled by Γ -PDF statistics
- Perspectives:
 - Further Improvements expected through Advanced Robustness Concepts & Individual Disturbance-Statistics/Flight
 - Extension into tactical range by combination with continuous optimizer for final approach
 - Inclusion of Disruptive Events Prediction into Scheduling by Combination with Dynamic Disturbance Models for Optimized Recovery Management



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