

Turnaround Prediction with Stochastic Process Times and Airport Specific Delay Pattern

An approach for a high reliable turnaround modeling and proof of concept with specific airport delays

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Abstract - The A-CDM's (Airport Collaborative Decision Making) goal of accurate turnaround time prediction is not met by traditional deterministic models. During this research, the influence of the stochastic arrival process on the turnaround process is captured by modeling stochastically all elements of the turnaround as part of a Ground Manager (GMAN). Since arrival delay is one major factor influencing turnaround time process duration and variance, and delay occurs in larger amplitudes at U.S. airports compared to European ones due the absence of slot control, the presented GMAN concept is tested with arrival delay data from the U.S. NAS (National Airspace System). The arrival delay is collected from ASPM (Aviation System Performance Metrics) and custom probability distributions were fitted on the data for different airport categories. The results obtained from this analysis by showing the proof of concept of the GMAN, are discussed in this paper

are no forecast or decision support systems available that can raise an alert about an impending or current process conflict (e.g.: fueling end time and boarding start time overlap). Currently, these conflicts are observed and dealt with in real time manually by operations and ramp agents.[11]

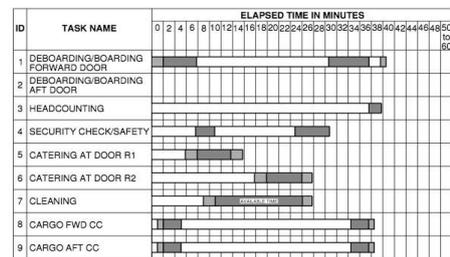


Figure 1. Example turnaround time schedule (extract) Airbus A319 [1]

Turnaround, prediction, processes, buffers, delay, A-CDM

I. MOTIVATION

The scheduled turnaround time (TTT) is defined as the time duration between In Block and Off Block times. The scheduled TTT duration may get affected if an aircraft does not arrive at the allocated position on time, or due to off-nominal variations sub-processes that constitute a turnaround processes. The standard turnaround plan comprises of various sub-processes (see Figure 1).

The aircraft operators and manufacturer derive TTT from deterministic sub-process (de-boarding, fueling, etc.) durations and their simple addition. This is not an accurate representation of reality because each of these sub-processes is stochastic and also, they are not always independent.

During off-nominal turnaround situations, i.e. in the presence of arrival delays or extended sub-process duration, the adherence to the scheduled TTT is not guaranteed. Moreover, airport type (large, medium, small) specific disturbances and ground handling staff skills may contribute to the punctuality in scheduled TTT conformity. In today's ground operations, there

Specifically airports with sophisticated data management inline with A-CDM have an exigency for accurate target times, i.e. target off block time (TOBT) prediction. It is foreseeable that the prescribed "best guess" system behavior by humans will no longer be accepted in a future 4D high precision flight trajectory environment. There are various process management tools which cover different phases of the flight, framing the proposed GMAN, see Figure 2:

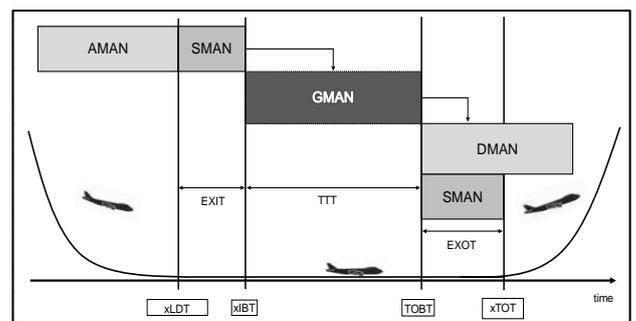


Figure 2. GMAN concept within adjacent ATM-tools inline with EUROCONTROL perspective

Within Europe arrivals are handled by the AMAN (Arrival Manager). The SMAN (Surface Manager) covers the ground movement of aircraft, but excluding turnaround (TA) while the DMAN (Departure Manager) covers the departure phase of the flight. There is actually no tool concept that covers the turnaround process,

The aim of this research is to no longer only understand the individual sub-processes that constitute a TA that were already subject to various research of the authors (see section II), but also understand the interaction principles between them in more detail. This was learnt to be reliable TTT prediction and strategically introducing control theories to not only predict but further minimize effects of disturbances in the overall TA process.

II. REVIEW

The GMAN concept (see chapter III) is an aggregated model, which is a result of various research activities at TU-Dresden focusing on aircraft turnaround, which are briefly recalled in the next sections. The pattern of arrival delays, which are used to test the GMAN with more realistic arrival delay assumption, is provided by the researchers at George Mason University (GMU).

A. Turnaround Research Activities at TUD

A previous study in cooperation with an aircraft manufacturer was conducted to understand turnaround reliability enhancements on a long time period on different German airports. Several technical deficiencies in aircraft design were observed, which contributed to uncertainty in TA. Also, based on representative interviews with ground handling experts, individual impact effects were linked to detailed aspects showing significant potential for improvement on TA-reliability for future aircraft design [2].

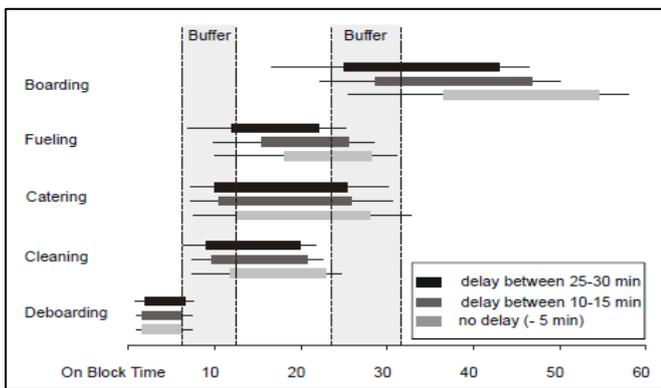


Figure 3. Process start times and duration correlating with delay [3]

Analysis of field data gathered as part of previous research activity at TUD has indicated that incoming aircraft delay (arrival delay) has a significant influence on the TTT. It has also been previously observed that airlines introduce dynamic scheduling buffers to mitigate the impact of off-nominal TTT on their schedule integrity (see **Error! Reference source not found.**). However, no systematic pattern of buffer introduction was deduced.

Our next study focused on analyzing the effect of airport type on the variation of different sub-processes that constitute a TA. A third category of airport called supply basis airports was established besides the regular hub and non-hub airport categories [4]. The turnaround process characteristic was observed to be distinct across different airport categories. The varying level of staff skills due to different training principles and expertise was identified as a major reason for distinct process characteristic [5]. Also, there have been several other studies focused on the stochastic modeling for TA sub-processes such as boarding, fuelling and cleaning [6][7][8].

To summarize based on previous research, the following facts are considered essential for the development of GMAN:

- The sub-processes comprising a TA should be modeled stochastically as they have uncertainty associated with their processes duration.
- The TA process is dependent on various parameters like airport category and operational factors (e.g. passenger number, airlines, aircraft type), and these information can be obtained from different sources.
- Incoming delay has an important influence on the individual sub-process duration and process interaction times (buffers).

B. Delay Modelling at GMU

The Center for Air Transportation Systems Research at GMU has conducted several studies to analyze delays in the U.S. National Airspace System (NAS). More recently, the research has focused on developing models to estimate passenger trip reliability metrics from the flight data [13][14][15][16][17]. Using the algorithms developed as part of this research effort, it is possible to link an arrival with the next departure and therefore model the turn-around process.

III. GMAN MODEL

The output of the GMAN concept described in this paper is the TTT, facilitating an accurate TOBT (Target Off Block Time) prediction based on the predicted or given In Block Time (IBT) and the turnaround time (TTT). In doing such a prediction, the duration of Look Ahead Time (LAT) is defined as a parameter that triggers the achievable accuracy of the TOBT prediction.

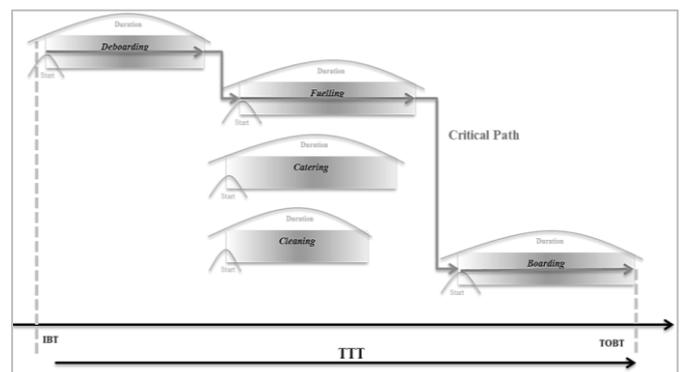


Figure 4. GMAN critical path calculation for one run out of n - with stochastic process start times and duration description

A. Process description

The total TTT is calculated by summation of the simulated sub-process durations considering process start times. Herin, the addition considers the dependencies of the longest process within the critical path of parallel and subsequent processes. The following sub-processes are considered: deboarding, catering, fuelling, cleaning, and boarding. Each of these processes is stochastically described with respect to their start time and process duration based on results gained in [3] and recalled in more detail hereafter. The start time of the first sub-process as an initial condition is directly taken as the In Block Time (IBT) (see Figure 4).

The end time of the current sub-process determines the start time of the next sub-process in the sequence of processes comprising each TA. As a result, when each sub-process is defined as a stochastic process, the start time of the next process is also variable. There are various alternatives of sampling the distribution of the current sub-process and deriving the start time of the next sub-process, e.g. using mean value, quantiles or median from the respective probability distribution which has been chosen previously (see Figure 5). Further research is required to ascertain which approach yields the best representation of reality.

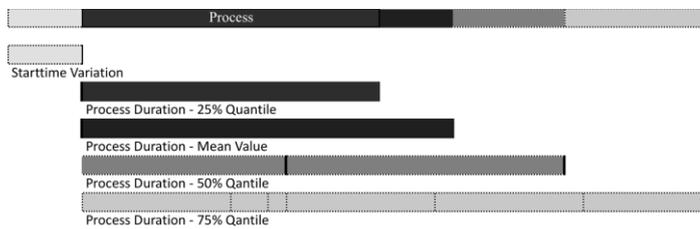


Figure 5. examples of possible process end times due to stochastic process start time and duration descriptions

To model the stochastic nature of the individual sub-processes, empirical data from aircraft operators, airports and ground handling companies is used. The data are categorized by airport type to capture the influence on the TA process and hence provide a more accurate prediction.[4] Finally, probability distribution functions can be fitted to the collected data. The GMAN tool is designed to allow using any of the following distribution functions:

- Deterministic
- Triangular distribution
- Gaussian distribution
- Weibull distribution
- Student-t-distribution
-

For most of the processes, Weibull distribution proved a reasonable fitting. The Gaussian distribution are used to describe the processes for which data was too limited for any more specific distribution fitting. In cases where none of the distributions provided a good fit but enough data points are available, box plots are used to sample the dataset. In cases where no empirical data was available, the deterministic description of the process from aircraft operators or manufacturers is used [6][7][8].

In order to more accurately model then the simple addition of deterministic durations the TTT, the influence of the following parameters on the TA process is captured, where inbound means the information connected to the arrival airport and outbound connected to the destination airport: (see Figure 6): [6][7][8]

- Aircraft type
- Airline
- Airport inbound and outbound
- Airport where the TA is processed
- Flight distance to destination
- Flight type, i.e. charter or business
- Incoming delay (on gate)
- Number of passengers inbound and outbound
- Type of aircraft stand

For each of these parameters, the relevant influence on TA process is defined by finding the correlation to specific process individual function fittings. The TA process distribution is also augmented by tags such as e.g. a connecting flight into a hub airport, where the tolerance level for a delay is expected to be lower than on other airports.

B. Critical Path

In order to predict the TTT, a critical path of the parallel and sequential processes running between IBT and OBT is constructed by the addition of the sub process times. Thereafter, the sampled process times along the critical path is summed up to obtain the total TTT, see Figure 4. The processes duration and start-times are sampled using Monte-Carlo simulations do gather a single date out of the stochastic descriptions. If within a single Monte Carlo run the process start time of a subsequent process is earlier than the end time of its predecessor, the start time of the subsequent process is shifted to the end of the leading process. It comes to:

- $TTT = (\text{start-time (deboarding)} + \text{duration (deboarding)}) + (\text{MAX process end-time of } ((\text{start-time (catering)} + \text{duration (catering)}) \text{ or } (\text{start-time ((fueling)} + \text{duration (fueling)}) \text{ or } (\text{start-time ((cleaning)} + \text{duration (cleaning)})) + \text{start-time ((boarding)+duration (boarding))})$
- $TOBT = IBT + TTT$

C. Look Ahead Time (LAT)

To reflect realistically the changing data quality used for TTT and TOBT prediction , four prediction levels are introduced, based on their valid lead time (Look Ahead Time - LAT). These levels along with the corresponding time horizons are:

- Basic (more than six months in advance of estimated IBT (EIBT))

- Strategic (between seven days and six months of EIBT)
- Tactical (up to seven days ahead of EIBT)
- Actual (after actual IBT(AIBT))

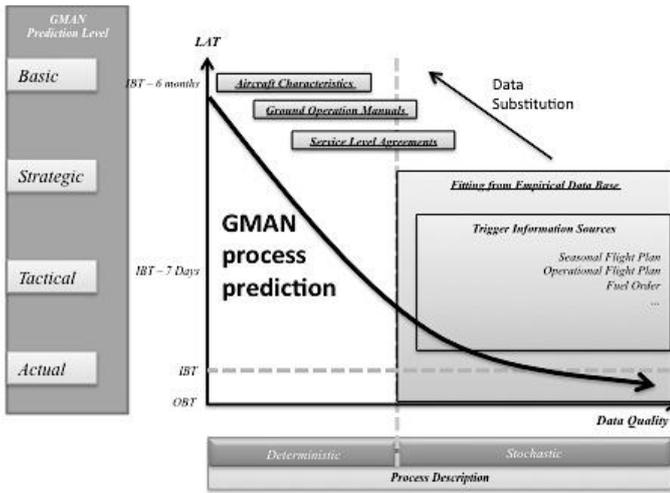


Figure 6: Sources for process description and Trigger Information for GMAN process prediction

A higher prediction accuracy level requires more reliable information. The basic level of prediction only requires aircraft characteristic, considering the lowest information level of available TTT planning. However the prediction at the *actual level* requires all essential characteristics to be known. With regard to the decreasing time horizons until reaching IBT and OBT, the quality of the data typically increases jump wise as better sensors come into play (e.g. Aircraft state downlink). Where the basic TTT are calculated roughly by using information out of standard documents, the actual TTT shall cope with specific operational figures to use the correlation stochastic process description.

While during the Basic level the deterministic process description is available from sources such as aircraft characteristics, ground operation manual or service level agreements, in the Actual level many more information sources can be used. In other words, as the LAT decreases, more accurate trigger information is expected to become available, and therefore a more specific stochastic process description out of the empirical database can be gathered and fitted (see Figure 6). Each prediction level can be abstracted from its predecessor and in the event of unavailability of required information; can be used as a fallback level. The more advanced the prediction level, the higher the accuracy in TTT prediction. [12]

D. Utility of GMAN

The development of a new model of TTT prediction compared to the usual best guess behavior was triggered by our field study of gathering turnaround data for various airports. The GMAN output may be used in ramp operations control or schedule planning the following ways:

- Perform Critical path analysis of TA process

- Analyze expected buffers between processes constituting a TA event
- Identify non-achievable target times at earliest times
- Identify excessive process durations

IV. DELAY MODELING FOR GMAN TEST

This section describes the data sources and the method used to sample arrival delays from historical data. When the LAT of TA prediction corresponds to the “actual” and “tactical” level, i.e. when the aircraft is already airborne to the GMAN-airport, the arrival delay (scheduled IBT – actual IBT) can be estimated from Flight Data Processing systems. In the event of lack of estimated arrival time prediction, the following attributes may be used to best predict delays:

- Airport
- Airport category (network function)
- Time of day/week/month/year
- Destination airport
- Airline

Firstly, the method to derive arrival delay distribution from the empirical data is described. Next, a method to derive daily delay pattern irrespective of time of day is presented due to that delays are distributed inhomogeneous over time. This analysis is done for four different airports; representing different airport categories (see [4]). The overall delay is represented in the GMAN by using a Monte Carlo simulation and categorized into tactical and/or strategic level of prediction. Observation of specific patterns over time, e.g. high delay at peaks at hub airports, is also accounted for in the delay modeling.

A. Data Source

The Aviation Safety Performance Metrics (ASPM) database provides detailed data on IFR (Instrument Flight Rules) flights and is maintained by the Federal Aviation Administration (FAA). The key fields of the “Individual Flights” table used in this research are scheduled and actual gate-in times (IBT) and the scheduled and actual gate-out times (Off Block Time - OBT).

The ASPM “individual flights” data was extracted for four airports (ATL, JFK, SJC, and BUF) for the time period starting at 00:00 am on 23rd July 2007 to 23:59 pm on 27th July 2007 (Monday to Friday). The start and end times are local time at the respective airports. The period of summer 2007 was chosen because it represents a period of historical high air traffic demand.

Gate arrival delay is calculated with respect to two different reference times, namely, scheduled (published) gate arrival time (Sch) and the gate arrival time according to the filed flight plan (FP). As expected, the mean arrival delay when the reference is the flight plan predicted gate arrival time is less than the mean arrival delay when the reference is published scheduled gate arrival time. The mean of arrival delays for the different airport and delay types is shown in Table 1.

The sample histogram in Figure 7 shows the distribution of gate arrival delay with respect to scheduled (blue) and flight

plan predicted (red) gate arrival times for ATL airport as an example. The dotted vertical lines of the corresponding colors represent the mean for both the cases, i.e. 12.16 minutes and 8.59 minutes respectively.

Table 1. Summary of ASPM Data analyzed (23rd July 2007 to 27th July 2007)

Airports	Number of Arrivals	Average Gate Arrival Delay (minutes)			
		All Flight		Only Delayed Flights	
		Sch	FP	Sch	FP
ATL	7347	12,16	8,59	16,35	13
JFK	2497	13,5	7,58	19,39	14,47
SJC	1084	9,14	5,44	13,35	10,14
BUF	644	17,49	13,6	22,2	18,42

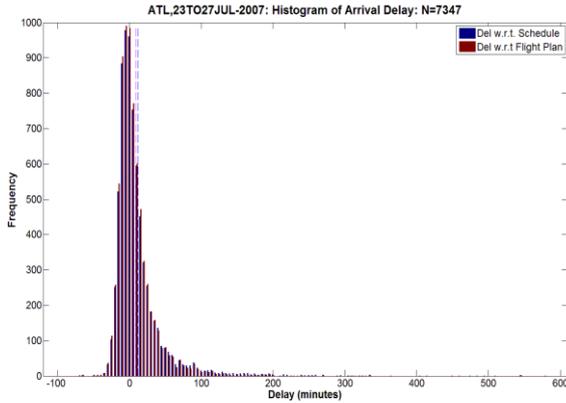


Figure 7. Distribution of Arrival Delay at ATL[8]

B. Overall Delay Modeling

The arrival delay data showed asymmetrical distribution about its mean value. Also, the positive and the negative delays (early arrivals) shows different pattern with the delayed flights having fatter tails as compared to the early arrivals. The same pattern is observed for the other three airports. Because of this asymmetry in the distribution of delay, distributions like normal, Weibull (shifted to ensure positivity) and t-distribution does not fit the data.

To deal with the asymmetry of positive and negative delays, the following modifications is done to the original dataset. Example dataset of arrival delays, $X = [1, 4, 6, 2, 0, 0, -2, -4, -10]$.

Firstly, the dataset is separated into positive (temp+) and negative (temp-) subsets. So for the given example, $Temp+ = [1, 4, 6, 2]$ and $Temp- = [-2, -4, -10]$.

Next, for each data point in both these subsets, append a value equal to the negative of that point into the set. Also, add points with zero (0) delays if any in the original dataset, to both these data subsets. Call these new datasets, $X+$ and $X-$. $X+ = [1, 4, 6, 2, 0, 0, -1, -4, -6, -2]$ and $X- = [-2, -4, -10, 0, 0, 2, 4, 10]$.

In order to use subsets $X+$ and $X-$ for simulation, the likelihood of non-negative and non-positive delay occurrences is required. Let $r+$ and $r-$ be the fraction of times distributions fitting data in $X+$ and $X-$ is to be used. It must be noted that $r+ + r-$ should be equal to 1. The values of $r+$ and $r-$ are given by the following equations:

$$r+ = \frac{n(Temp+) + 0.5 * Nz}{n(X)}$$

where Nz is the number of zero delay points (2 in this case) in the original dataset, and $n(X)$ is the cardinality of set X . Similarly,

$$r- = \frac{n(Temp-) + 0.5 * Nz}{n(X)}$$

It can be verified that $r++r-=1$. For this example, $r+ = (4+1)/9$ and $r- = (3+1)/2$.

The values of r obtained for the data used in this research is shown in Table 2.

Table 2: Values of $r+$ and $r-$ to be used to positive or negative delay distribution selection

Airports	Sch		FP	
	$r+$	$r-$	$r+$	$r-$
ATL	0.55	0.45	0.54	0.46
JFK	0.58	0.42	0.55	0.45
SJC	0.51	0.49	0.48	0.52
BUF	0.57	0.43	0.57	0.43

Table 3: Distribution parameters for the non-negative delays

Airports	Sch			FP		
	Normal Fit	Weibull Fit	Student t-fit	Normal Fit	Weibull Fit	Student t-fit
	(mu, std)	(scale, shape)	degree of freedom	(mu, std)	(scale, shape)	degree of freedom
ATL	(0,56.01)	(24.59,7.68)	(1.48)	(0,41.3)	(18.21,8.71)	(1.84)
JFK	(0,60.34)	(26.66,8.36)	(1.79)	(0,40.93)	(16.88,6.33)	(2.45)
SJC	(0,41.43)	(17.05,6.28)	(1.81)	(0,30.62)	(11.77,4.76)	(2.36)
BUF	(0,62.25)	(25.58,6.51)	(1.65)	(0,49.77)	(19.74,5.47)	(1.92)

After isolating the positive and negative values into separate sets, distributions were fitted to the data. Normal, Weibull and student-t distributions were used. The parameters obtained are shown in Table 3 and Table 4 for the non-negative and the non-positive delays respectively.

For all the cases, student t-distribution provided the best fit, with the Kolmogorov-Minnow-Test (KS-Test) failing to reject the null-hypothesis for a p-value of 0.05.

Table 4: Distribution parameters for the non-positive delays

Airports	Sch			FP		
	Normal Fit	Weibull Fit	Student t-fit	Normal Fit	Weibull Fit	Student t-fit
	(mu, std)	(scale, shape)	degree of freedom	(mu, std)	(scale, shape)	degree of freedom
ATL	(0,11.56)	(4.81,6.24)	(49.42)	(0,11.97)	(4.96,6.18)	(18.07)
JFK	(0,23.98)	(10.99,7.76)	(4.32)	(0,26.97)	(12.04,7.65)	(3.18)
SJC	(0,11.6)	(4.65,5.56)	(4.89)	(0,13.57)	(5.7,6.77)	(3.65)
BUF	(0,13.34)	(4.41,3.09)	(212978, 3.17)	(0,13.51)	(4.42,3.07)	(97347, 9.68)

In order to generate delays for simulation, the following scheme is used:

1. Select either "Sch" or "FP" type of delays. "Sch" arrival delays are with respect to the scheduled (published) arrival times and are higher than "FP" flight delay, which is measured with respect to the flight plan, predicted arrival time of a flight.

2. Arrival delay (say x) is drawn from the non-negative delay distribution with corresponding parameters (as shown in Table 3) with $r+$ likelihood and from the non-positive delay distribution with corresponding parameters (as shown in Table 4) with the remaining $(1-r+)$ likelihood.

For example: For ATL airport, for “FP” type of delay, using student-t distribution, the delay (say x) is generated using the following scheme:

$$x = \begin{cases} |T(1.84)|, & \text{with 0.54 probability, and} \\ -|T(18.07)|, & \text{with 0.46 probability} \end{cases}$$

where $T(a)$ is a student t-distribution with ‘a’ degrees of freedom and $|a|$ represents the absolute value of ‘a’.

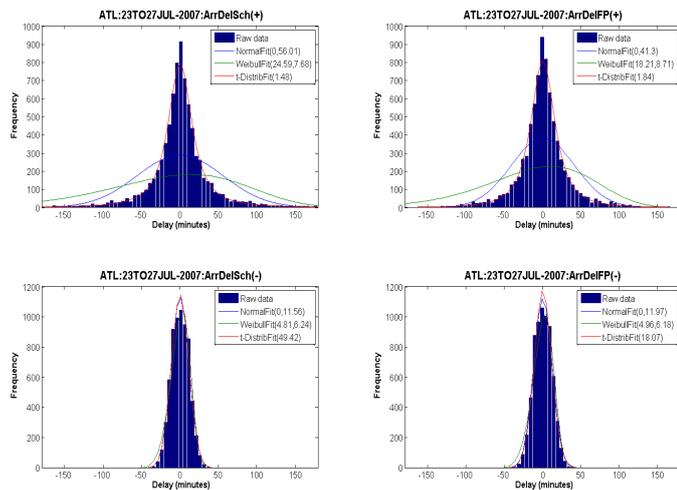


Figure 8: Distribution fit for the Positive and Negative Delays for ATL [8]

The distribution fit for non-negative and non-positive delays with respect to published schedule and flight plan based arrival time is shown in Figure 8 for ATL. Similar distribution fits were plotted for the other airports but are not included here. The student t-distribution fits the data best and passes the K-S test with p value of 0.05 for all the airports.

C. Delay pattern over time of day

In order to identify the relationship of arrival delays with the time of day, the ASPM data for a 24 hour period was filtered for the four airports used in this part of the study. The objective was to test the hypothesis that delays at hub airports peaks with the increase in the number of active aircraft on the airport surface according to queuing theory.

The plots in Figure 9 show the relationship between mean arrival delay and the time of day for ATL, JFK, SJC and BUF for 26th July 2007. The second axis (green) on each plot shows the number of aircraft that are at the airport surface in the corresponding time bin (15 min intervals).

For ATL (top-left plot) - a hub airport, the mean arrival delay (including early arrivals) is always greater than zero from the morning peak (32nd quarter, 8 AM local time) till the evening peak and fluctuates with the variation in the number of active aircraft on the airport surface.

The active number of aircrafts at JFK – also a hub airport - shows higher fluctuation when compared to ATL, with distinct morning and evening peak traffic. There is a trough in the

number of operations between quarters 38 to 50 (9:30 AM to 12:30 PM). The mean arrival delay at JFK also follows this trend in traffic with lower average values than that at ATL.

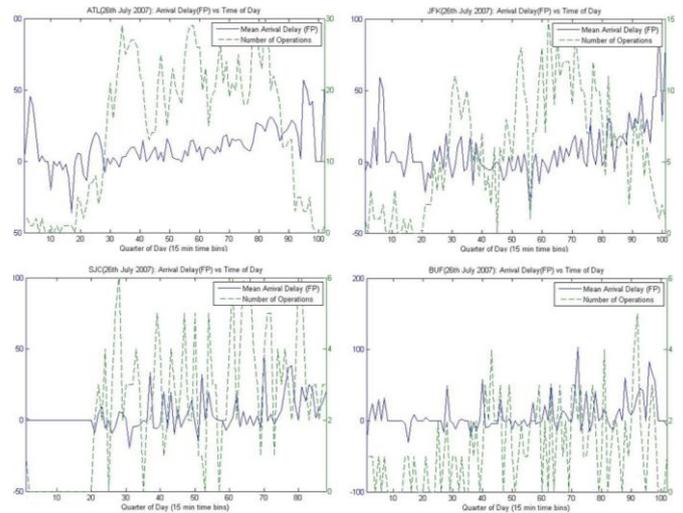


Figure 9. Variation of Arrival Delay with respect to Time of Day for ATL, JFK, SJC and BUF

For both the non-hub airports, SJC and BUF, the number of active aircraft throughout the day fluctuates considerably with multiple peaks and troughs. The arrival delay also doesn’t follow any distinct pattern. This may also be attributed to the fewer number of flights in one day worth of data presented here.

In order to be used in the GMAN environment, this analysis will be repeated with data from more than one day, i.e. over several weeks to gather meaningful peak trends in the data.

Due to the fact of lack of data for European airport, we use the US data source for our following GMAN proof of concept. We are aware of potential conflicts caused by different operational constrains (e.g. slot coordination, ground delay programs, penalty box concept) which will be analyzed subsequently in our research, as shown in Figure 10. This fact is however no critical condition for the GMAN concept testing as discussed in this paper (see above).

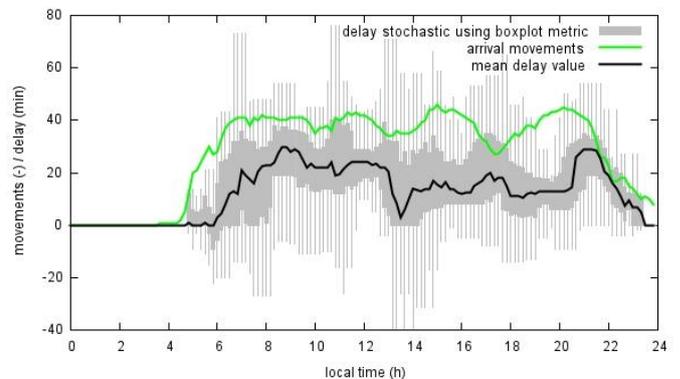


Figure 10: Example Delay Pattern of FRA (12th Oct. 2011)

Figure 10 shows first results for the delay data for one day (12th October 2011) at Frankfurt, Germany using floating hours for the analysis. It aggregates the results as found for the U.S. airports in figures 9 and 8: While the green line shows the inbounds over the day, the grey lines show the respective delay variations for ten minute bins along the floating hours.

To cope with the stochastic deviations, while trying to find mean full pattern, we use a common box plot metric, which consists of a descriptive five number summary [18]: sample minimum, first quartile (Q1), median, third quartile (Q3), and sample maximum. In accordance to [19] we use the inter quartile range (IQR) to constrain the minimum value (minimum = MAX (Q3 + 1.5 (Q3-Q1), sample minimum)) and the maximum value (maximum = MIN (Q1 - 1.5 (Q3-Q1), sample maximum)).

V. GMAN PROOF OF CONCEPTS

The GMAN model has been implemented as a Java application. The current capability of the prototype includes the necessary logic and steps to predict the TTT as described in Section III, as well as an output in terms of a box plot for each TA sub-process.

The prototype was used to investigate four scenarios representing different levels of LAT for a single generic flight. For this flight the stochastic process description was gathered from a database at TU-Dresden that includes several thousand TA instances at German airports. Data from all the airports and airlines was aggregated because sufficient data was not available for every category desirable for TTT prediction.

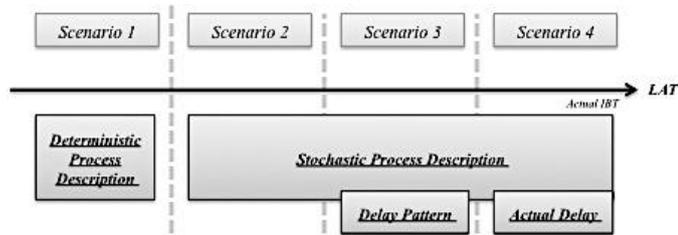


Figure 11. GMAN Proof of Concept Scenarios with corresponding inputs

Each of the four scenarios uses different data inputs - see Figure 11. Scenario 1 represents the Basic GMAN level where deterministic process descriptions are used, in scenario 2 these are replaced by stochastic descriptions. Scenario 3 uses modified stochastic process descriptions corresponding to a given predicted delay out of a delay pattern. Within scenario 4 another stochastic process description is used due to the fact of a given actual delay.

The Monte Carlo simulation is repeated n-times (n=10,000 default) for each scenario. For each sub-process the duration is sampled from the distribution fitted on the empirical dataset. The mean value of the duration time obtained by sampling the data is used. If the sum of this mean value of process duration and the start time of the corresponding process exceeds the start-time of the following process in the critical path, the start time of the following process is replaced by this summation. Table 6 shows the mean and the 75% quantile values obtained as a result of performing these Monte Carlo simulations.

All simulation results are presented by four stochastic parameters: 25% quantile (Q_{.25}), 50% quantile (modus), 75% quantile, and mean value. The definition of quantile means that x% of the scenarios points out a smaller process time. So, between Q_{.25} and Q_{.75} 50% all scenarios are located. The difference between modus and mean indicates the displacement

of the functions climax and can therefore give hints to a more reliable process and TTT prediction.

Scenario 1 represents the basic level LAT where all process descriptions are deterministic (trigger information: Airbus A319, IBT= 07:00), it is based on Airbus' airplane characteristics.

Table 5: process parameters GMAN test scenario 1

	Start (time)	Durations and Times			
		Q _{.25} (mm:ss)	Mean (mm:ss)	Q _{.50} (mm:ss)	Q _{.75} (mm:ss)
IBT	07:00 h				
Deboarding	07:02 h	/	06:00	/	/
Catering	07:08 h	/	18:00	/	/
Fuelling	07:08 h	/	07:00	/	/
Cleaning	07:11 h	/	15:00	/	/
Boarding	07:31 h	/	07:00	/	/
TOBT (time)			07:38 h		
TTT			38 min		

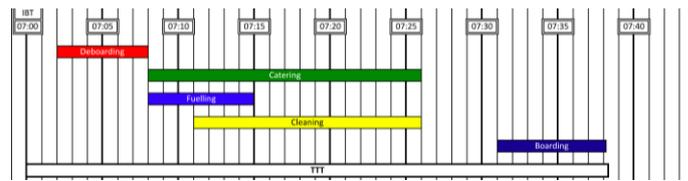


Figure 12. GMAN test scenario 1 processes over time

Due to the deterministic process description no variation of processes is visible in scenario 1 (see Figure 11 and Table 5).

Scenario 2 represents strategic level LAT where all process descriptions are stochastic (trigger information: Airbus A319, Airline XYZ, terminal stand, IBT= 07:00), based on fitted TUD-data base.

Table 6. process parameters GMAN test scenario 2

	Start (time)	Duration and Times			
		Q _{.25} (mm:ss)	Mean (mm:ss)	Q _{.50} (mm:ss)	Q _{.75} (mm:ss)
IBT	07:00 h				
Deboarding	07:01 h	4:25	05:08	5:09	6:10
Catering	07:08 h	5:50	06:20	6:35	8:15
Fuelling	07:08 h	5:05	05:27	5:15	7:28
Cleaning	07:09 h	7:10	07:29	7:52	8:10
Boarding	07:25 h	6:12	06:48	7:06	8:51
TOBT (time)		07:31 h	07:32 h	07:33 h	07:35 h
TTT		31 min	32 min	33 min	35 min

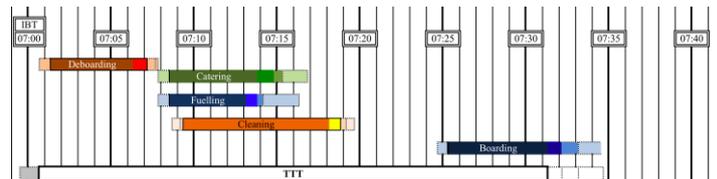


Figure 13. GMAN test scenario 2 processes over time

In scenario 2 the possibilities in using stochastic process descriptions are clearly visible. Possible buffers and critical paths are visible while that is not possible with deterministic process descriptions. Different possibilities of TTT are calculated, depending on the desired reliability.

Scenario 3 represents strategic level LAT where all process descriptions are stochastic and due to specific delay pattern these descriptions have changed (trigger information: Airbus

A319, Airline XYZ, terminal stand, using Monte Carlo simulation for delay (normal distributed for non-hub-airport, 3 classes of process distributions, I.: delay ≤ 5 min, II.:delay <5 min & ≤ 20 min, III.: delay > 20 min), process description based on fitted TUD-data base.

Table 7. process parameters GMAN test scenario 3

	(time)	Durations and Times				
		Start (time)	Q _{.25} (mm:ss)	Mean (mm:ss)	Q _{.50} (mm:ss)	Q _{.75} (mm:ss)
IBT	07:00 h	07:06 h				
Deboarding		07:07 h	4:30	04:59	05:00	06:01
Catering		07:14 h	5:20	05:54	06:00	07:28
Fuelling		07:14 h	4:52	05:10	05:07	06:48
Cleaning		07:15 h	4:21	06:48	07:00	07:59
Boarding		07:30 h	5:59	06:20	06:29	07:42
TOBT (time)			07:36	07:37 h	07:37 h	07:38 h
TTT			30 min	31 min	31 min	32 min

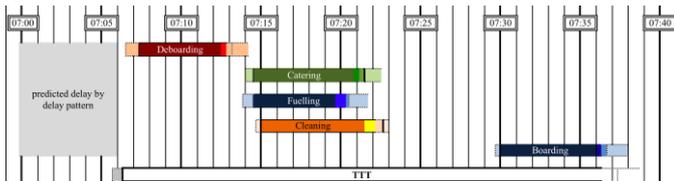


Figure 14. GMAN test scenario 3 processes over time

By the use of different process descriptions for different classes of incoming delay for each of the ‘n’ Monte Carlo simulations, the TTT and the process durations are different from the non-delayed predictions. Here it is possible to see in advance how the buffers, critical path and the process durations change due to a possible delay.

Scenario 4 represents actual level LAT where all process descriptions are stochastic and due to actual delay time, known by ATM system, their descriptions have changed from scenario 2 and 3 (trigger information: Airbus A319, Airline XYZ, terminal stand, delay=15 minutes leading to IBT= 07:15), process description based on fitted TUD-data base.

Table 8. process parameters GMAN test scenario 4

	(time)	Durations and Times				
		Start (time)	Q _{.25} (time)	Mean (time)	Q _{.50} (time)	Q _{.75} (time)
IBT	07:15 h					
Deboarding		07:16 h	3:15	03:21	03:22	04:01
Catering		07:21 h	5:50	06:05	06:09	07:06
Fuelling		07:21 h	4:15	04:51	04:36	06:36
Cleaning		07:21 h	6:20	07:12	07:31	08:50
Boarding		07:32 h	5:05	05:29	05:30	07:27
TOBT (time)			7:37	07:38 h	07:38 h	07:40 h
TTT			22 min	23 min	23 min	25 min

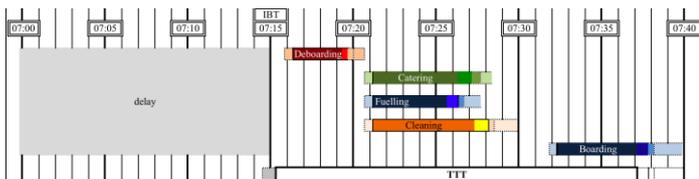


Figure 15. GMAN test scenario 4 processes over time

Scenario 4 illustrates in comparison to scenario 2 the changed process descriptions when a delay is predicted. Thus the start times and durations of some process change, also possible buffers within the critical path and at last also the TTT.

Table 8. Scenario comparison

	TTT Duration and Times			
	Q _{.25}	Mean	Q _{.50}	Q _{.75}
Scenario 1		38 min		
Scenario 2	31 min	32 min	33 min	35 min
Scenario 3	30 min	31 min	31 min	32 min
Scenario 4	22 min	23 min	23 min	25 min

Table 8 shows the different TTT in different reliability zones for all scenarios and. In scenario 1 there is only one (=38 min) deterministic time prediction. Beginning with scenario 2 a confidence interval of TTT prediction can be used due to the stochastic prediction approach. The reliability of prediction increases if wider qantiles as boarders are used, but the uncertainty increases too. The influence of different delays to the process conduction is visible when comparing scenario 3 and 4. While in scenario 3 only a small delay was proposed bb the pattern, in scenario 4 the actual delay was significant higher. As result the TTT was smaller. To scope with this problem a good delay modeling is necessary. Although a shorter TTT is better in the first look, for efficient logistics and planning a more reliable prediction, e.g. at an A-CDM airport, is better. The different LAT levels do not generally imply that the TA process times will get smaller by default (or even shows a smaller variation). But the reliability of the results increases significantly. So it is possible that a higher process time and higher variance come along with increasing input data quality.

Our proof-concept implementation points out the workability of the GMAN model. The dynamic IBT are not taken into account, but we will focus on their specific influence during our further research.

VI. INSIGHTS AND FUTURE WORK

The next step in this research is to test the GMAN on a live airport environment instead of testing it using static empirical data. In order to facilitate this, cooperation with a German airport is scheduled where in the initial phase, several weeks of TA process durations will be recorded. The GMAN implementation will be run in shadow mode, derive operational concepts to cope with the different quality of input data. Next, distribution functions will be fitted for the recorded TA processes. And finally the GMAN tool will be validated by comparing its prediction of TTT with the live airport operation.

Also further delay analysis will be conducted at TUD using historical flight data for several European airports spanning over duration of 6 years. The objective will be to use the methods of delay analysis described in this paper to discover specific delay patterns with respect to time of day and/or airport category.

The ultimate objective of this research is to identify a generic set of strategies on when and where to intervene in the TA process when disturbances or non-achievable target times occur. The idea is to use closed loop control theory with varying control strategies to influence the TA process when required. Furthermore we are investigating if general delay pattern to specific airport categories can be applied, by using American and European flight data.

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