Development of Stochastic Delay Cost Functions

Prediction of delay propagation under uncertainty for tactical airline schedule recovery

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***Abstract*—When a disturbance cannot be absorbed by schedule buffer, the tactical schedule recovery process of an airline prioritises between flights. This considers the cost of delay and may result in a reallocation of scarce airport resources during turnaround. Delay cost reference values do not differentiate between specific flights but rather aircraft types. This article presents a method to develop flight-specific delay cost functions, which consider inherent absorption capacities and downstream uncertainties. Delay propagation trees are used to model airline resource interdependencies and derives the associated cost of downstream delay cost-drivers from dependent probabilities using operational data. In a case study setting, the resulting stochastic cost functions are compared against reference values per aircraft type and deterministic step-cost functions per flight.**

***Keywords*—delay propagation; airline ground operations; flight prioritisation; schedule recovery; stochastic delay cost**

I. Introduction

Airlines derive different business utilities (e.g., revenue generation) from individual flights in their network. This utility depends on network structure, flight schedules, airport performance, resource assignments and sold origin and destination (O&D) itineraries (with or without transfer connections). Given that the latter two are changing on a daily basis, notwithstanding a fair degree of commonality, flight utility cannot be regarded as fixed.

Airlines which operate hub-and-spoke networks typically have more heterogeneous flight utilities than carriers in point-to-point networks, given that, for example, regional and feeder traffic is brought to the hub with smaller aircraft, with passengers transferring onto long-haul flights operated by widebody aircraft, and, indeed, with transfers from the long-haul flights onto onward connections beyond the hub. This requires a mixed fleet and results in a variety of passenger types per flight. Another reason for this heterogeneity are economies of scope in a hubbed network. Customers from many markets and with multiple flight legs may fly together on the same flight, which often implies higher fares and potentially higher compensation and reimbursement to be paid by the airline in case of schedule disruptions (cf. EU Regulation 261/2004 [1]).

The utility of a flight is an important factor for airlines when dealing with deviations to the original flight plan on the day of operations, commonly referred to as tactical schedule recovery. It allows airlines to prioritise among various affected aircraft, especially with regard to their ground time, given that they are all subject to the limited availability of airport / ground handling resources. While for some airlines this prioritisation is defined at the strategic or pre-tactical level (i.e., before the day of operations), many airlines have dedicated schedule recovery units (i.e., Airline Operations Control Centres - AOCCs) which decide upon the assignment of resources and recovery options on a day-by-day basis. Others may operate variants of this approach. Cited in high-level documents such as SESAR's ATM Master Plan in 2015 [2], European researchers and policy makers have identified that such AOCCs need to contribute their flight priorities in order to collaboratively achieve improved ATM network performance. Due to data sensitivity, *costs* are usually absent from implemented airport collaborative decision-making (A-CDM; [3]) solutions, such that a common valuation framework for individual flight utilities is still lacking.

A. Status Quo

Recovery decisions within an AOCC are usually elaborated manually and are often fragmented, since various agents conduct *department-specific* assessments of how a schedule deviation may impact their area of operations (e.g., passenger connections). If a deviation occurs to the original schedule, *department-specific* solutions are calculated with, for example, the help of database query-systems and collected at the desk of the manager on duty [4]. It is up to the experience of the respective operator to assemble a feasible recovery decision, which satisfies the constraints of all involved departments and stakeholders. Given the setting at major hub airports, where during so-called hub-banks, or waves, up to 100 aircraft of the same airline are turned around within a time frame of about three hours, this can be a highly iterative and lengthy procedure and is unlikely to result in cost-minimal solutions. Consequently, many research projects aim at an integration and partial automation of the decision-making process in an AOCC. Therein, different approaches can be identified, so that: (i) some scholars attribute more recovery potential to the tactical tail and crew assignments, i.e. swapping resources between flights or cancelling flight cycles in order to mitigate schedule disturbances [4]–[10], (ii) few explore the possibility of purposely delaying aircraft at-gate to ensure passenger transfer in comparison to speeding up flight segments with higher cost indices [11]–[13], while (iii) others consider the turnaround to be the major recovery option, given the possibility to shorten or omit entire sub-processes, or assign extra resources to speed up standard operating procedures [14]–[19]. Further differentiation can be made for the incorporated objectives. Some studies aim at minimising delay as the departure time offset from the schedule [17], [19], [20], while others set out to optimise the associated cost of delay [4]–[6], [8]–[11], [18]. A balanced approach of delay management by coupling turnaround and trajectory optimisation based on delay costs has also been developed [21]. In this context, the possibility to incorporate both different flight utilities and the progressive increase of costs associated with the magnitude of departure delay is a requirement [22], [23].

Established reference values for airline delay costs in Europe are available [23], with the next update due in 2021. These published values, although cited for 'low', 'base' and 'high' cost scenarios, are averaged for fifteen aircraft types and designed, for example for high-level cost benefit analyses, e.g. at the network level. These reference values demonstrate monotonic, increasing delay cost functions. Underlying cost steps, largely driven by Regulation 261 [1], are smoothed by statistical fits and the effects of delay recovery through schedule buffer [23]. In operational practice, for individual flights, these functions have sudden rises in cost due to missed transfer connections, night curfews, maintenance events, and crew duty time regulations. The report (*ibid.*) indeed flags that caution should be used in using high-level averages for explicit case trade-offs, e.g. specific prioritisations between particular flights. Despite the need of accurate step-cost functions for the validation of the user-driven prioritisation process (UDPP) as part of the SESAR programme, for example, such functions can only be statistically estimated, mostly due to data confidentiality reasons [24]. Furthermore, associated uncertainties have been neglected in most previous research.

B. *Focus and Structure*

We herein demonstrate flight-specific delay cost functions, which incorporate the uncertainties related to downstream events (aircraft, crew and passenger-related). A case study applies stochastic cost functions and compares the resulting recovery decisions with those calculated using reference (statistical) and step-linear delay cost functions. Associated benefits for airline schedule recovery are discussed.

Our contribution is structured as follows: Sec. II summarises the state of the art in modelling network delay propagation. Sec. III describes the methodology for building stochastic delay cost functions. Sec. IV implements flight-specific cost functions in a tactical schedule recovery model. In Sec. V, stochastic delay cost functions are applied in a case study setting, comparing them with reference and step-linear cost functions. Sec. VI presents the results of the analysis. Sec.VII draws conclusions and discusses potential future research.

II. Modelling Delay Propagation

Delay propagation describes the chain effects following a deviation, greater than the inherent absorption capacities (such as schedule buffer), carried downstream, e.g. onto further nodes in the transport system. In the case of airline networks, delay can be propagated by aircraft rotations (i.e., rotational reactionary delay) or by different aircraft due to passenger or crew transfer interdependencies (i.e., non-rotational reactionary delay) [23]. At about 45%, reactionary delay represents the largest cause of departure delay in Europe [25], displaying this same approximate ratio for many years. A common metric to determine the impact of a disruption in a given airline network is the 'delay multiplier'. This describes the ratio of reactionary to primary delay. Larger values obtain for larger disruptions (e.g., more buffers are exceeded) which occur in morning hours (resources have more remaining tasks scheduled downstream) [26].

A. *Delay Propagation Trees*

Delay propagation has been studied mainly retrospectively by building delay propagation trees with recorded timestamps from actual operations. Along with the delay multiplier as a measure of magnitude, further metrics have been introduced to characterise the impact of deviations on a flight-by-flight basis, such as severity (i.e., number of additionally affected flights) and depth (i.e., highest number of downstream legs impacted by propagated delay) [27]. Thereby, initial models, which considered a limited scope of resource dependencies, bounded the depth horizon to the immediate next (two) flight leg(s) (rotations) and assumed block times to be static (see Fig. 1 and supporting caption) as well as independent and identically distributed (IID). This was refined later: recent models apply, for example, stochastic, non-IID block times and delay propagation trees with Bayesian networks, which enables the calculation of conditional probabilities for specific resources to contribute to the delay of a given flight [28].

Airlines continuously optimise their flight schedules by redistributing buffer capacities and synchronising aircraft and crew schedules to compensate for frequent delays and limit non-rotational delay propagation [29], [30]. Furthermore, robust fleet assignment strategies have been developed which aim at reducing the severity of a disturbance by assigning aircraft to fly short cycles from the hub (i.e., only two legs, towards an out-station and directly back), thus limiting the geographical scope in which a fleet is operating [31].

B. *Back- and Network-Propagation*

Back-propagation describes the effect when a flight is suffering from reactionary delay that was initially caused or propagated at the departure airport earlier in the day. It is driven by short cycles from a central hub, given that aircraft tend to have reduced ground times at out-stations and limited in-flight recovery potential on regional routes. Given that many hub airlines have implemented short cycles into their schedules in recent years, back-propagation is mostly experienced at major hub airports. However, individual chain

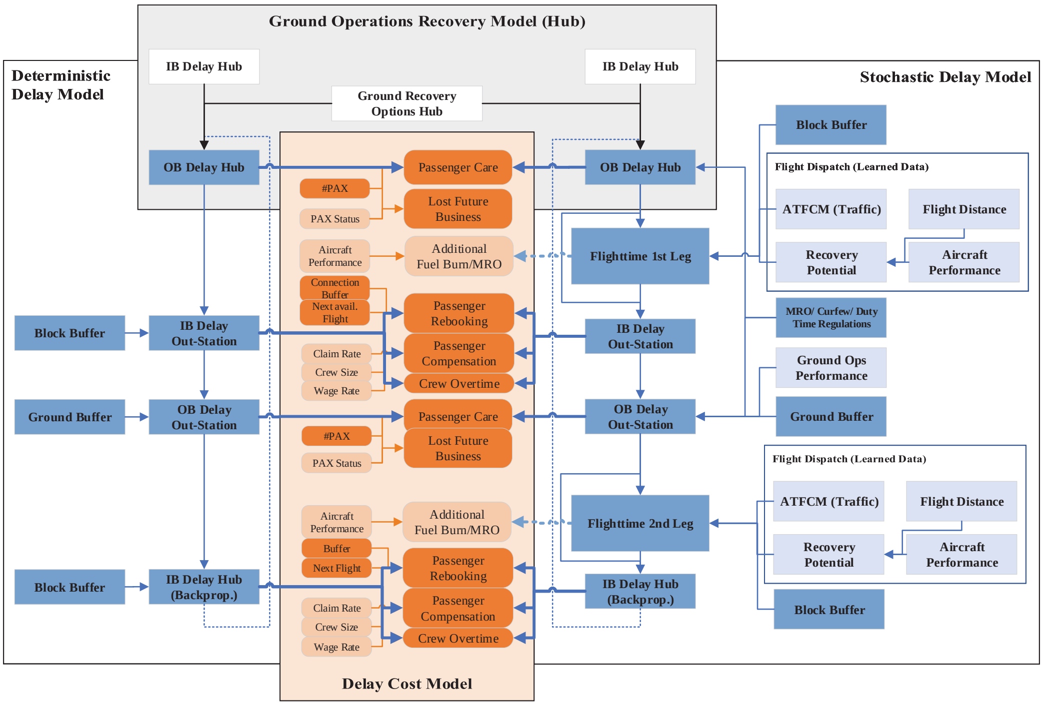


Figure 1. Framework of stochastic delay cost as a complement to the ground operations recovery model. For better trade-off decisions between ground recovery and OB delay, downstream uncertainties are considered regarding how OB delay will propagate along aircraft rotations. Dependencies from muted boxes are derived from field data.

effects to and from individual airports appear to be volatile on a daily basis, considering different resource schedules and passenger itineraries [32]. Another major determinant is the number of transfer connections originating from a disrupted flight (i.e., the connectivity index). The more outbound flights an inbound flight is feeding with transfer passengers, the higher the potential propagation effect and a disturbance can quickly spill from one (hub) airport to others in the respective airline/alliance network [31].

C. *Stochastic Delay Propagation*

Given the stochastic nature of the air transport system, it is difficult to estimate the full extent of delay propagation during tactical operations. Thereby, the uncertainty to be considered increases with the depth of the potential propagation (i.e., the look-ahead time horizon). Post-operational analysis frequently update delay multipliers or deploy delay cost reference values. The latter, as stated, have been modelled for different aircraft types, including, fuel, crew, maintenance and passenger 'hard' (e.g., care, rebooking, compensation) and 'soft' (market share attributable to punctuality) costs [23], but are not intended for flight-specific models. Consequently, existing stochastic delay propagation models have been adopted and extended in this research.

III. Stochastic Delay Cost Model

A. *Methodology*

The stochastic delay cost model built complements the already developed ground operations recovery model (see Fig. 1), which is briefly introduced in Sec. IV. The extended model incorporates stochastic block times for the first and second rotation of a short cycle, which depend on outbound (OB) delay, inherent block-time buffers, air traffic flow and capacity management (ATFCM) regulations and in-flight recovery potential.

The conjoint impact of all four independent variables is derived from block-time data of the summer season, 2019. Ground-time buffers and ground operations performance at the out-station, as well as maintenance constraints, night curfews and duty time regulations, are considered in the estimation of how a given outbound delay at the hub propagates into inbound delay at the OS, hence to outbound delay at the OS and, finally, back propagates to the initial hub.

Based on these four milestones, potential delay costs incurred by the airline are derived. Delay cost values per passenger are deduced from the reference source [33], considering that not all passengers decide to wait for alternative flights or claim their entitled compensation. The potential loss of future business from a given delay (i.e., the passenger soft cost) is retrieved from the same report, considering the respective aircraft types. Similarly, crew wage rates are retrieved from [34] and adjusted for inflation. Whilst fuel burn is currently not included in these cost models, this important issue is discussed at the end of paper, in the conclusions and future work of Sec.VII.

B. Stochastic Delay Cost Functions

For the calculation of a stochastic delay cost function, deterministic cost functions are estimated for each inbound milestone of an upcoming cycle. These cost functions have linear segments and event-related cost drivers. Linear segments are influenced by aircraft type, crew overtime, maintenance expenses and passenger soft costs, while abrupt cost steps obtain due to missed transfer connections at the destination airport, overrun crew duty times or interference with night curfew or scheduled maintenance events. Note that although some of the linear cost-drivers may show polynomial shapes (e.g., soft costs [33]), they are herein linearised within 5-minute intervals, in which they are estimated with steady slopes. For the prediction of how much outbound delay is propagated to the next airport during the block time, multiple stochastic block- and cycle-time distributions are fitted from field data, which are categorised according to the respective outbound delay (t_{OB}) at the flight origin airport. Fig. 2 shows three exemplary inbound delay distributions which are likely to occur after outbound delays of 20, 25 and 30 minutes and each result into one cost estimate per delay category.

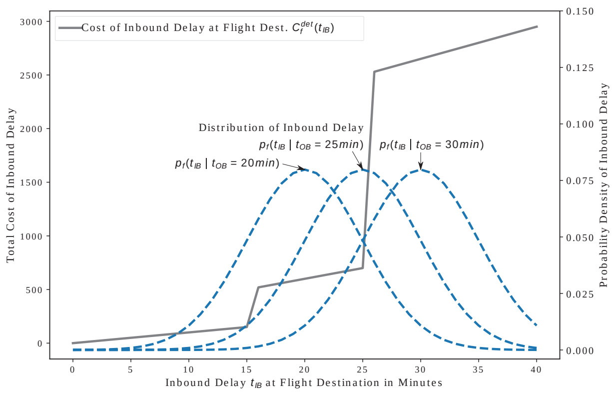
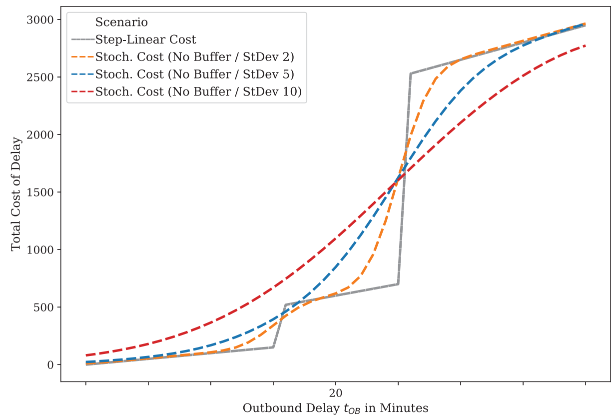


Figure 2. Integration of inbound delay cost with stochastic block times.

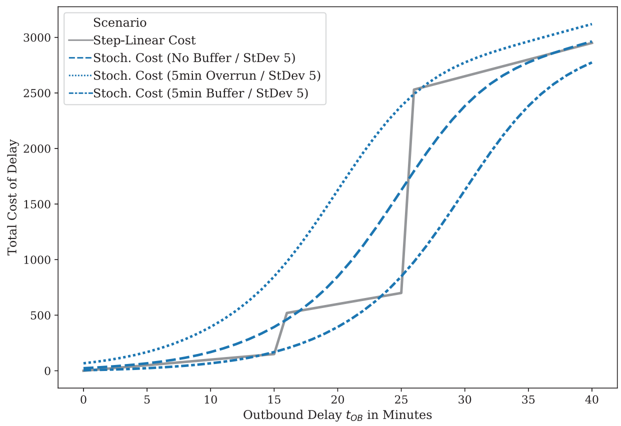
In full detail, for a given flight f, the deterministic function of inbound delay cost $C_f^{det}(t_{IB})$ and the dependent probability density function $p_f(t_{IB} \mid t_{OB})$ of an inbound delay (t_{IB}) occurring after an outbound delay (t_{OB}), are multiplied, so that the integral defines the stochastic cost estimation C_f^{sto} for the respective outbound delay category (1).

$$C_f^{sto}(t_{OB}) = \int p_f(t_{IB} \mid t_{OB}) \cdot C_f^{det}(t_{IB})\, dt_{IB} \qquad (1)$$

Note that at this step we assume normal distributions with constant variance for the inbound delay at flight destination to describe the general concept of our approach. This is independent of the true stochastic nature of a particular flight, where we typically find best fits with beta or Weibull distributions. In any case, smaller standard deviations result in stochastic delay cost functions that closely fit the shape of the deterministic cost curves, whereas large standard deviations smooth the curve along the x-axis (see Fig. 3a). If the scheduled block time comprises buffer times, the stochastic cost curve is shifted towards the right on the x-axis, whereas actual block times that exceed the scheduled period cause a dislocation towards the left (see Fig. 3b). Depending on the block-time characteristics of a specific flight, multiple parameters can interfere with another and distort the stochastic function in the directions described. To consider cost drivers at multiple downstream milestones (see Fig. 1), cost functions for each milestone can be stacked to create the stochastic delay cost function of a full flight cycle from the hub.



(a) Stochastic delay cost with different standard deviations for aircraft block time.



(b) Stochastic delay cost with different buffer times within scheduled block time.

Figure 3. Stochastic impact of block time parameters on step-cost function.

IV. Implementation into Airline Schedule Recovery

As described, stochastic delay cost functions may support tactical airline schedule recovery, so that scarce resources, especially during turnaround, can be assigned preferably to those aircraft from whose subsequent flights the airline is likely to incur higher costs of delay. Thus, stochastic functions described in the previous section are implemented into a scheduling model for tactical airline ground operations recovery, described in full detail in [35].

A. Airline Ground Operations Recovery

The applied tactical airline ground operations recovery model is based on an extension of the resource constraint project scheduling problem (RCPSP) such that it aims at assigning a limited set of airport resources to a set of aircraft A. Thus, the turnaround sub-processes TP for each related aircraft ($RA_i = a$) are scheduled in a way that the total costs from a given disruption are minimised. Thereby, "in-block" as the first process of each turnaround ($i \in IB \subset P$) can only be scheduled after the estimated in-block time $EIBT_a$. Further sub-processes can only start (s_i) once all preceding processes are (scheduled to be) completed. Predecessor and successor relationships are defined in the precedence matrix $PM \subseteq P \times P$.

Selected airport resources enable schedule recovery options ω_i, which accelerate the duration D_i of specific turnaround sub-processes $i \in P$ (e.g., quick de-boarding via two doors is enabled once an aircraft is allocated to a remote position). Further recovery options include stand reallocation, quick turnaround (e.g., accelerated cabin cleaning, catering and loading due to additional staff), arrival prioritisation (i.e., aircraft receive priority during approach or taxi-in from air traffic control), expedited passenger transfer (e.g., transfer passenger groups are transported with dedicated buses to their departure gate), deploying stand-by crew (e.g., substitution of a delayed transfer crew with a stand-by), and rebooking of passengers onto alternative flights. The latter two can be described as the elimination of process dependencies, rather than as process acceleration. In any case, for most recovery options, a recovery cost C_i^{rec} is incurred by every application, which relate to additional ground handling fees or costs of rebooking, etc. (The various forms of resilience (absorptive, adaptive, and restorative) are discussed in the ATM context, with quantified cost examples, in [36].)

As also explored in [32], aircraft can be held on position in order to maintain passenger transfer connections which induce departure delay v_a once the scheduled off-block time $SOBT_a$ is overrun. In the deterministic delay cost model, the respective cost of delay is incurred as linear segments S, with constant marginal delay costs C_{as}^{lin} for durations of five delay minutes r_{as} each, and step costs C_{as}^{stp} once the delay exceeds a certain threshold, which is activated by $y_{as} \in 0, 1$. In the stochastic delay cost model, no step costs need to be considered, and polynomial cost functions are linearised for five-minute segments S, also with constant marginal delay costs C_{as}^{lin}. Missed ATFM slots are discussed in Sec.VII.

B. Mathematical Formulation

$$\min \sum_{a\in A}\sum_{s\in S}\left(C_{as}^{lin}\; v_{as} \;+\; C_{as}^{stp}\; y_{as}\right) + \sum_{i\in P} C_i^{rec}\;\omega_i \qquad (2)$$

$$\text{s.t.} \quad s_i \geq EIBT_a \qquad \forall\, i \in IB, RA_i = a \qquad (3)$$

$$s_i \leq SOBT_a + v_a \qquad \forall\, i \in OB, RA_i = a \qquad (4)$$

$$s_j \geq s_i + D_i - \omega_i M \qquad \forall\, i,j \in P \mid PM_{i,j} = 1 \qquad (5)$$

$$v_a = \sum_{s\in S} r_{as} \qquad \forall\, a \in A \qquad (6)$$

$$r_{as} \geq (U_{as} - L_{as})\, y_{as} \qquad \forall\, a \in A; \forall\, s \in S \qquad (7)$$

$$r_{as} \leq (U_{as} - L_{as})\, y_{a(s-1)} \qquad \forall\, a \in A; \forall\, s \in S \qquad (8)$$

The objective function (2) is to minimise the total cost related to a deviation to the original schedule, which corresponds to the sum of delay costs across all linear segments and all overrun step-cost thresholds. The final term in the objective function comprises all costs incurred by applied schedule recovery options. The start of each turnaround can only be scheduled after the respective EIBT (3). If the calculated off-block time overruns the SOBT, the delay is induced as described in (4). Scheduling constraints (5) ensure that each sub-process can only start once all preceding processes have been finished, apart from when a recovery option was applied for this process. Constraints (6-8) distribute the off-block delay across the pre-defined segments, whereby the delay in each segment is bounded and delay can only be induced in later segments, when the step cost for the respective segment is also accounted for. For a more detailed description of the model, please refer to [18], [35].

V. Scenario and Application

The tactical airline ground operations recovery model is applied in three different versions to a case study comprising 15 turnarounds during a morning peak at Frankfurt airport (FRA). Model version 1 incorporates delay cost reference values per aircraft type as determined from [23]. Model version 2 applies deterministic, step-linear cost functions, which consider cost drivers of the subsequent flight cycle. Model version 3 adopts the stochastic delay cost functions as described in Sec. III. All three models are used to solve arrival delay deviations for all 15 aircraft, as they appeared on a selected scenario day during the summer season of 2019.

A. Case Study Setting

Flight plan data are adapted from the summer schedule of 2019, of a local hub carrier. Passenger connections are simulated to resemble potential itineraries that adhere to the average connection ratio (55% transfer passengers) and minimum connecting time at FRA (45 minutes), typical airline load factors (85%) and avoiding extreme detours (e.g., passengers from MAD are unlikely to connect via FRA to BCN).

Crew connections and stand allocations are built with separate optimisation algorithms, such that they comply with official operational constraints. Contact stands in Terminal 1A (Stands A1, A2, A3 and A5 in Fig. 4) are reserved for flights to and from Schengen countries only. Contact stands with special security and customs areas (Stands A3, A6, B1 and C1) can also operate flights to and from non-Schengen countries.

Stands A3 and A6 are predominantly used for intercontinental flights with widebody aircraft. Stands R1 and R2 are remote, whereby passengers need to be transferred with apron buses via the central bus station (marked with a bus icon in Fig. 4).

Three aircraft, including two widebodies, are fixed at their initial stands due to operational constraints, whereas the remaining twelve aircraft can be re-allocated to any other stand complying with the required O&D security procedures. In total, one arrival prioritisation request ($C^{Rec} = 0$; currently without a fuel burn assessment), one quick turnaround unit ($C^{Rec} = 500$ per turnaround), two quick transfer buses ($C^{Rec} = 100$ per passenger group transfer fee) and one standby crew ($C^{Rec} = 1000$; two additional hours) enable the respective schedule recovery options.

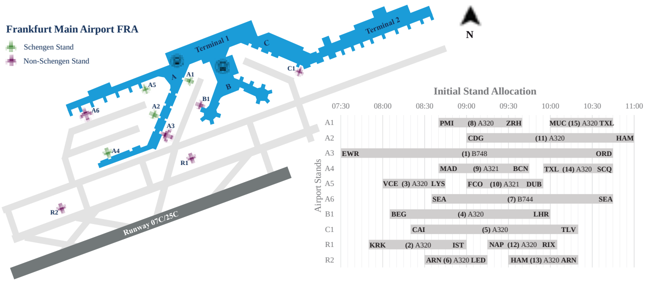
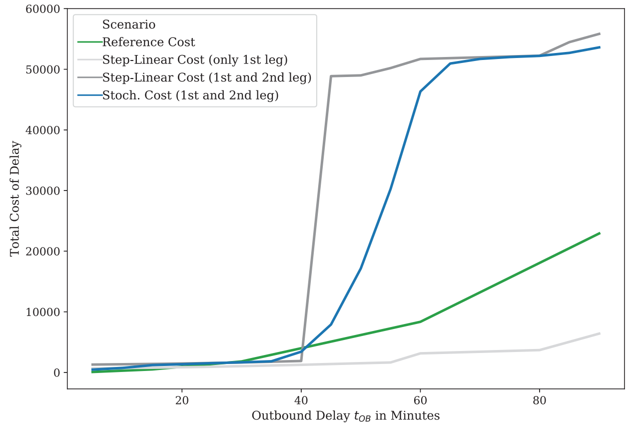


Figure 4. Case study setting at Frankfurt airport (FRA).

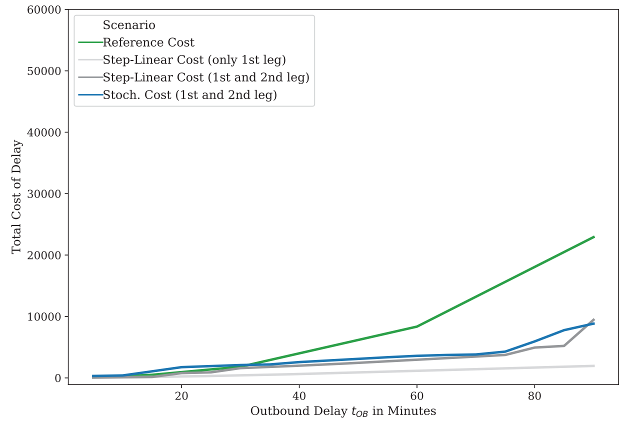
B. *Flight-Specific Delay Costs*

In each version of the model, an individual delay cost function is incorporated for all outbound flights. In model 1, functions are only differentiated according to aircraft type, such that flights with similar aircraft are associated with equal reference delay cost curves. The function is thus interpolated with linear segments between the reference cost values described in [23] (see green lines in Fig. 5).

For model 2, separate deterministic cost functions are built with respect to the first and second legs of the next flight cycle. Linear and event-related cost drivers are identified for the corresponding aircraft, crew and passenger itineraries, such that, for each event, the associated buffer time is calculated until it would impact the schedule, which is then translated into the respective linear costs and cost steps (see Fig. 6). Light grey lines in Fig. 5a and 5b show the resulting cost functions after the first leg. Note that the cost function of the flight to Stockholm (ARN) contains more cost steps, given that passengers can miss onward connections there, operated as part of the partner airline hub network (see Fig. 6). No transfer connections have been sold via London Heathrow (LHR), so that no potential rebooking and/or compensation costs need to be considered there. Dark grey lines in Fig. 5a and 5b show back-propagation costs, which are incurred after the second leg of the flight cycle. Here, both functions contain cost steps, given that all inbound flights to FRA carry transfer passenger. Furthermore, Fig. 5a includes the special case where the aircraft operating to ARN has a maintenance event scheduled after the cycle, which under no conditions can be missed. Thus,



(a) Total cost of delay for flight cycle to alliance partners' hub-airport in Stockholm (ARN) with onward connections.



(b) Total cost of delay for flight cycle to outstation in London Heathrow (LHR) without any onward connections.

Figure 5. Stochastic impact of downstream block-time parameters on step-linear cost function in comparison to reference delay cost.

if outbound delay before the cycle exceeds the schedule buffer between the cycle end and the maintenance event, the cycle would need to be cancelled (aircraft swaps are not considered in this example). Hence, the very large cost step after 40 minutes of outbound delay results from passenger delays of 3-8 hours downstream (depending on the alternative flight connection), resulting in numerous Regulation 261 obligations, including rebookings and compensation payments.

Model 3 adopts the deterministic cost functions for both cycle legs from the second model and integrates them with the respective block-time distributions as described in 1. Blue lines in Fig. 5 show the resulting stochastic cost functions. Note in Fig. 5a that due to block-time buffer, the sharp increase related to the maintenance event is shifted towards a later time (cf. 3b), such that the first flight could be assigned with additional outbound delay. In this specific instance, the stochastic function considers that in five out of six cases, at least ten minutes of delay can be absorbed during the block time (83%-quantile), such that only one sixth of the total costs of not operating these flights (i.e., the cancellation

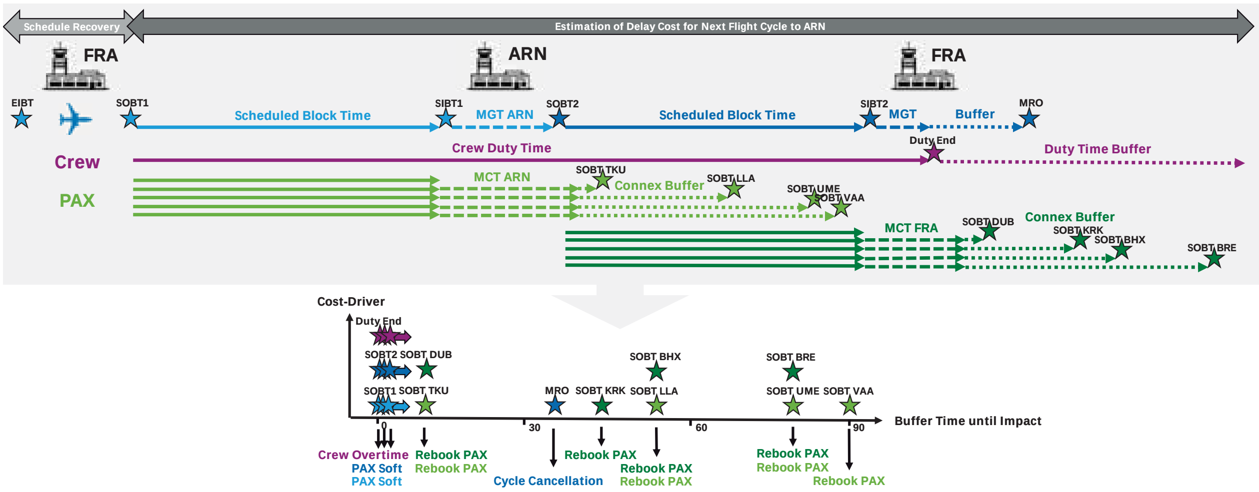


Figure 6. Cost driving events considered (and their inferred buffer times) for building the deterministic delay cost function for flight cycles to ARN.

costs) are taken into account. Note in Fig. 5b that block times to LHR are very tight, which means that outbound delay is likely to induce additional inbound delay after the cycle, instead of mitigating it. The stochastic function captures this by consistently overestimating the deterministic curves (cf. Fig. 3b).

VI. Results

A sensitivity analysis was performed for a scenario day with average inbound delay of 19.5 minutes (St.Dev. = 33, Min. = -12, Max. = 108) across all 15 aircraft. Within this already stressed operational setting, the inbound delay for aircraft 13 (flying to Stockholm (ARN)) is increased from no outbound delay to 70 minutes, respecting that a critical maintenance event is scheduled with 40 minutes buffer time after the flight cycle (see Fig. 5a). Thus, the output of the ground operations recovery model is analysed *ceteris paribus* for each level of inbound delay of the respective aircraft, in order to see how the system behaves with different delay cost functions when a (very) large cost impact is expected downstream.

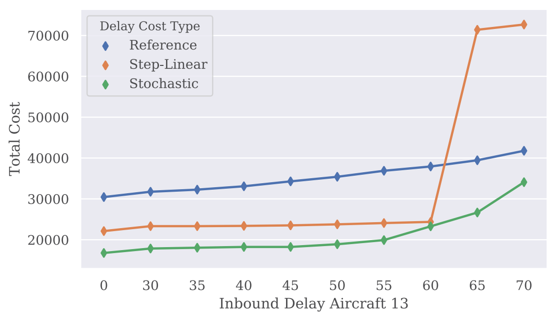


Figure 7. Total cost output of tactical airline schedule recovery model.

A. *Total Cost*

For up to 60 minutes of inbound delay, the highest total costs obtain with the reference cost functions. With the step-cost model, costs increase suddenly once the inbound delay of aircraft 13 exceeds 60 minutes, which results in a flight cancellation to ARN (due to the incompatibility with the critical maintenance event, even when specific turnaround processes are accelerated). The total costs calculated with the stochastic delay cost model are roughly half of those of the reference delay model. Once inbound delays of aircraft 13 exceed 60 minutes, they rise progressively due to the increased probability that the delay cannot be recovered and the flight has to be cancelled (cf. Fig. 7).

B. *Stability of Decision Variables*

Fig. 8 shows the outbound delay of all aircraft when inbound delays of up to 70 minutes are introduced for aircraft 13 on the selected scenario day. Comparable outputs with all three versions of the delay cost models are shown, highlighting divergent behaviour at critical events, such as the scheduled maintenance check of aircraft 13, which has 40 minutes of buffer time after the rotation to ARN (see Fig. 5a). Given the average cost basis, the reference delay cost model does not consider the (explicit) maintenance event, such that inbound delay of aircraft 13 is propagated almost directly proportionally, resulting in a linear increase of outbound delay, which was only reduced by 8 minutes of ground buffer time. The model with step-linear delay costs considers the critical 40-minute threshold of outbound delay, such that it assigns recovery resources to aircraft 13 for inbound delays of up to 60 minutes. Due to the required minimum turnaround time, even higher inbound delays cannot be recovered so that the flight is considered as cancelled, which produces significant disruptions for other aircraft. In contrast, the stochastic delay cost model allows outbound delays higher than 40 minutes, by considering the block time buffers and historic flight time variances within the rotation to ARN. The optimal level of outbound delay for the other aircraft is thus more variable, as are the decisions regarding which passenger connections should be maintained (see Fig. 9).

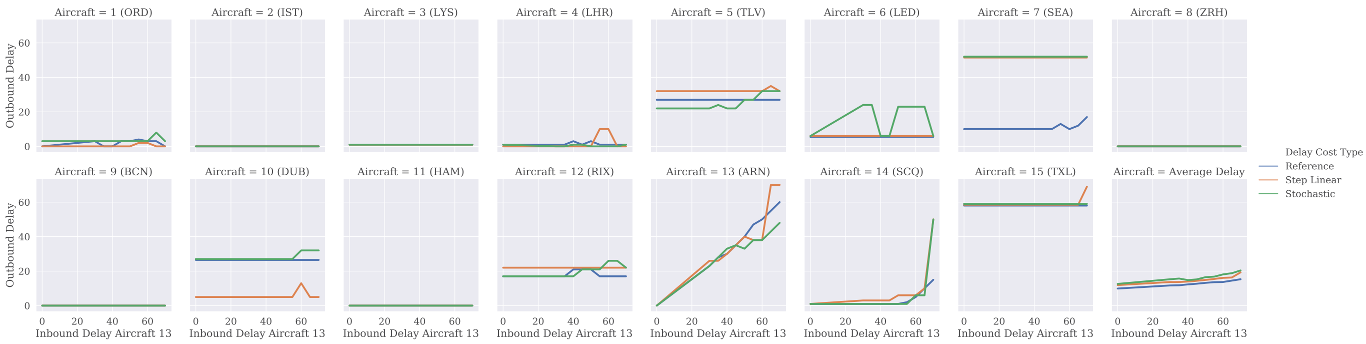


Figure 8. Sensitivity analysis of the selected scenario day - outbound delay of all aircraft.

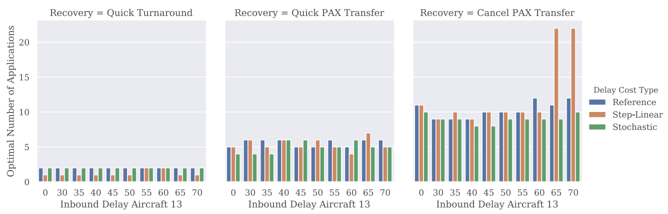


Figure 9. Optimal number of applied recovery options.

On average, the stochastic delay cost function model allows additional flexibility to wait for delayed transfer passengers. This induces more outbound delay, given that absorptive capacities in downstream operations are incorporated, but can save, on average, the loss of at least one passenger transfer connection (see Fig. 9). Similar trade-offs in a stochastic model were observed in [32]. The step-linear delay cost model produces higher outbound delays than the reference cost model, as it assigns more delay to flights that incur the lowest cost. A prominent example for this case is aircraft 7, flying to Seattle-Tacoma (a route with few alternative flights for transfer passengers and high cycle buffers), which is delayed by 52 minutes in the step-linear and stochastic cost models, such that it can await delay transfer passengers. In contrast, the reference cost model solely respects the average, higher costs of delay for the operating widebody aircraft, such that it assigns a quick turnaround to aircraft 7 and releases it with just 12 minutes of outbound delay.

The results for aircraft 10, flying to Dublin, highlight some of the downsides of the step-linear cost model. Due to tight transfer dependencies, two large step costs occur after only 5- and 10-minute buffer times, such that the aircraft departs with only 5 minutes of delay. In reality, there seems to be sufficient buffer time within the flight cycle to recover higher outbound delays, such that the stochastic delay model waits for transfer passengers and assigns 27 minutes of delay. In general, marginal linear costs per delay minute are smaller within step-linear cost functions (considering that event-related costs are incurred as one fixed delay value), such that a quick turnaround is not an optimal option for some delayed aircraft, given that the additional resources incur more costs than can be saved by reducing the outbound delay (cf. reduced number of quick turnarounds in Fig. 9). In the case of more than 60 minutes of inbound delay to ARN, and thus a flight cancellation, the number of cancelled passenger transfers doubles in this model.

Mindful of recently introduced mechanisms for ATFM-airline cooperation, such as UDPP, which require flight-specific priority/ranking values, the calculated outbound sequence is analysed. As shown in Fig. 10, the results of the model with reference delay costs lack selectivity between ranks 9-14, which can be attributed to similar SOBTs and delay cost values of the respective aircraft. In contrast, the outbound sequence with step-linear delay costs is very stable, such that only the causal aircraft 13 is shifting positions towards later times, until it is cancelled. However, considering the calculated sequence with the stochastic cost model, it becomes clear that there is much more uncertainty in the system than in the step-linear model, once the inbound delay of aircraft 13 exceeds 60 minutes.

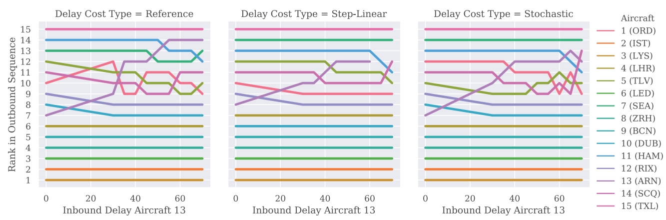


Figure 10. Rank of outbound flights.

VII. Conclusions and Future Work

This article presented the development of stochastic delay cost functions to predict delay propagation under uncertainty. The sensitivity analysis has shown that optimal recovery decisions based on stochastic delay costs are less robust in comparison to those calculated with step-linear delay costs (especially with regard to outbound delay and passenger transfer management), such that they require accurate supporting forecast data. However, the higher stability of optimal recovery decisions calculated with (deterministic) step-linear delay cost functions is misleading, given that such a model does not incorporate downstream uncertainties or buffer capacities. Consequently, in the step-linear model, results are prone to deliver excessive total cost estimations once critical cost-driving events are determined as inevitable. In contrast, stochastic delay costs increase the flexibility for schedule recovery by using buffer capacities downstream, which creates the need to coordinate potentially higher outbound delay values for some aircraft with ATFM slots in subsequent research.

Further challenges remain regarding the determination of actual buffers deployed by airlines. Nevertheless, the approach adopted here is not dissimilar to substantial operational practice. Additionally, the *cost* of such buffers (available in [23]) may be used to evaluate resilience metrics such as those introduced in [36]. Complementarily, evaluating the cost of uncertainty would make a valuable contribution to the SESAR Performance Framework.

Changes recently made to Regulation 261 regarding connections at outstations beyond Europe, and proposed changes regarding intra-European connections, are important elements to consider to capture the changing regulatory landscape and can be easily incorporated into the proposed model. Further research should also analyse the general behaviour of the model around major cost steps, especially in the context of UDPP, whereby airlines can only provide normalised, discrete priority values. A transfer of the optimal turnaround recovery into such priority values is yet to be made. This work will be complemented with the addition of full fuel burn assessments, including dynamic cost indexing [37], as demonstrated in [12], and currently being explored, for example, within the Clean Sky programme.

ACKNOWLEDGMENT

This project has received funding from the German Federal Ministry of Economic Affairs and Energy (BMWI) within the LUFO-V project OPsTIMAL under grant agreement No 20X1711M. Further funding was received from the SESAR Joint Undertaking under the European Union's Horizon 2020 research and innovation programme under grant agreement No 783287 (Engage KTN). The opinions expressed herein reflect the authors' views only. Under no circumstances shall the SESAR Joint Undertaking be responsible for any use that may be made of the information contained herein.

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