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A NOVEL APPROACH FOR TURNAROUND TIME ALLOCATION BASED ON REINFORCEMENT LEARNING

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Abstract

Airport ground processes are a critical path in the air traffic network. The management and reliability of the scheduled turnaround time is essential for the system's robustness and efficiency. This paper presents a method based on approximate dynamic programming and reinforcement learning to optimize airline policies regarding the scheduling of turnaround times. The model uses arrival delay and the airport level of congestion as state variables, while the turnaround time is the control variable. The feedback control approach is capable to adapt the proposed policy to changes in the system, which is a key feature due to the non-linear, stochastic and time-varying nature of airport operations. Moreover, the methodology provides a decision-making rule and not only a static optimal value. The cost function of the method considers delay and "buffer" costs, but also costs related to perturbations in schedule adherence, internal (local) delays and airport level of congestion. This approach widens the turnaround time allocation problem to a system-level view. The method is applied to a case study in a busy European airport, where the dataset covers approximately 34,000 turnaround operations. We focus the analysis on two carriers with different business models. Results show that an accurate use of turnaround time allocation methods may help airlines to manage the punctuality performance of turnaround aircraft by minimizing system costs.

Keywords: airport operations; delay management; airline scheduling; dynamic programming; feedback control

1. Introduction and motivation

Airports are the nodes that interconnect flights in the complex air traffic networks [1]. Hence, airport ground processes are a critical path of this system: incoming aircraft continue on the subsequent legs of their planned itineraries and crew members and passengers connect to other flights or other transport modes [2], [3]. An incident at the airport environment may easily propagate through the network and generate system-level effects, like reactionary delays [4]–[6]. Airport ground operations mainly consists of the handling procedures at the stand (de-boarding, catering, fueling, cleaning, boarding, unloading and loading), which are defined as the aircraft turnaround [7]. Therefore, the management and reliability of the scheduled turnaround time become essential as regards to the system's robustness and efficiency [3], [8]. Moreover, from an air transportation system view, uncertainties in airport operations have huge impacts on flight schedule adherence [9], [10]. Instead of following the traditional gate-to-gate framework, the air-to-air approach focusses on the ground trajectory of an aircraft, in order to enable efficient flight operations and reliable departure times [11]. Predictability of an accurate TOBT (Target Off-Block Time) represents one of the basic challenges regarding the new operational concept associated to 4D trajectory based operations [12]–[14]. The demand of high arrival punctuality at destination through an adjusted CTA (Controlled Time of Arrival) requires precise scheduling from the initial ground phase of a flight, as arrival punctuality is clearly driven by departure punctuality [11], [15]. Therefore, turnaround time allocation and predictability of departure times are key elements to avoid perturbations on trajectory schedule adherence [16], [17] and system reliability [18]. Once different initiatives have successfully decreased airborne delay over the two last decades, the next opportunity for time-efficiency improvement rely on airport surface operations [19].

Nevertheless, airports are limited in capacity by operational constraints and different factors such as traffic mix, runway configuration, local weather or wake separation [20]. Imbalances between capacity and demand can lead to congestion problems [21], which have worsened due to the strong growth in the number of airport operations during the last decades [22]–[24]. The objective of this paper is to provide a novel methodology to manage turnaround times and departure schedule allocation, by also considering airport congestion.

Since information management and data analytics are becoming strategic issues for the efficiency of the global air traffic management system [14], there is an opportunity to develop new conceptual tools based on artificial intelligence and machine learning. In the case of airport operations, this new tools can be applied to solve traditional scheduling and resource allocation problems, by considering the potential of these techniques for data science [25]. Airports act as dynamic and complex systems, with several facilities, processes and stakeholders that are interrelated and interact with each other [8]. In order to provide a holistic approach for the future “intelligent airport systems”, the new conceptual tools should not pursue isolated views but integrated ones; specially when solving problems like flight delay prediction, passenger profiling, traffic segmentation and supply chain optimization [26]–[28]. Regarding the turnaround scheduling problem, apart from airline strategies, new tools should also consider airport characteristics, like the level of congestion [29].

Reinforcement learning methods are based on the idea that the output of the system is a sequence of actions, as part of a global policy [30]. The system evolves and there is no such thing as the best action in any intermediate state; an action is good if it is part of a good policy. Appraising the changes in the system, these methods are able to assess the goodness of strategies and learn from past good action sequences, in order to generate an optimal policy. This policy also changes the system state, so a feedback control approach is developed [31]. This dynamic programming approach fits perfectly with the turnaround time allocation problem, where external conditions (as inbound delays or airport congestion) can affect the system’s response.

Section 2 reviews the background information regarding turnaround management and presents our contribution. In Section 3, we state the problem characteristics and detail the proposed optimization model. Section 4 describes and discusses the main results for the case study. Finally, Section 5 appraises the conclusions, the model applicability, and the potential further work.

2. Background and contribution

The Airport Transit View (ATV) concept analyses the “visit” of an aircraft to the airport [12]. This framework connects inbound and outbound flights, providing a tool to optimize airport operations and to enable a more efficient and cost-effective deployment of operator resources. It also changes the conceptual framework from the gate-to-gate approach to the air-to-air conception. Whereas the gate-to-gate process is more focused on the airborne phase of the aircraft trajectory, the air-to-air appraisal concentrates on the airport ground operations between flight segment/legs [32], [33]. Figure 1 illustrates the ATV domain: the operational attention relies on ground processes when optimizing resources and seeking time-efficiency improvements.

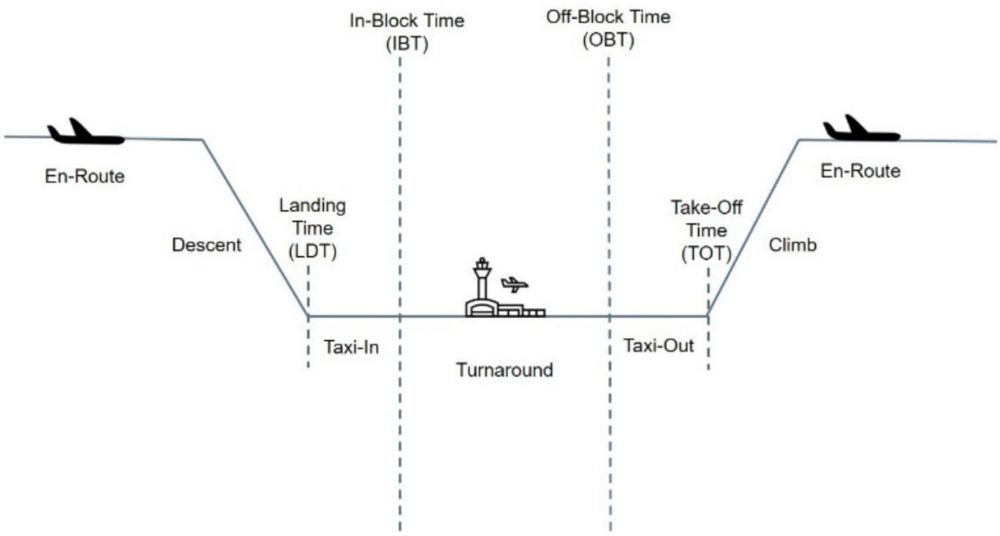


Figure 1. ATV air-to-air concept (not to scale).

Aircraft turnaround refers to the process of servicing an aircraft on the ground between two consecutive flight segments. The turnaround consists of five major tasks related to aircraft ground handling (Figure 2): de-boarding, catering, cleaning, fueling and boarding as well as the parallel processes of unloading and loading cargo [7]. It may also include aircraft programmed maintenance. The minimum time needed for turnaround operations depends on the aircraft type, the airline business model, the airport configuration and the handling agent characteristics. From the operator perspective, all these handling processes will follow defined procedures. The Airplane Characteristics for Airport Planning manual (Figure 2) stablishes a minimum recommended turnaround time for each aircraft type and configuration. Nevertheless, uncertainty of operational conditions (e.g., runway configuration, aircraft performances, air traffic control procedures, regulations, airline strategies, available ground resources and meteorological conditions) makes on-ground operations a stochastic phenomenon and provides turnaround with a time-varying and random nature.

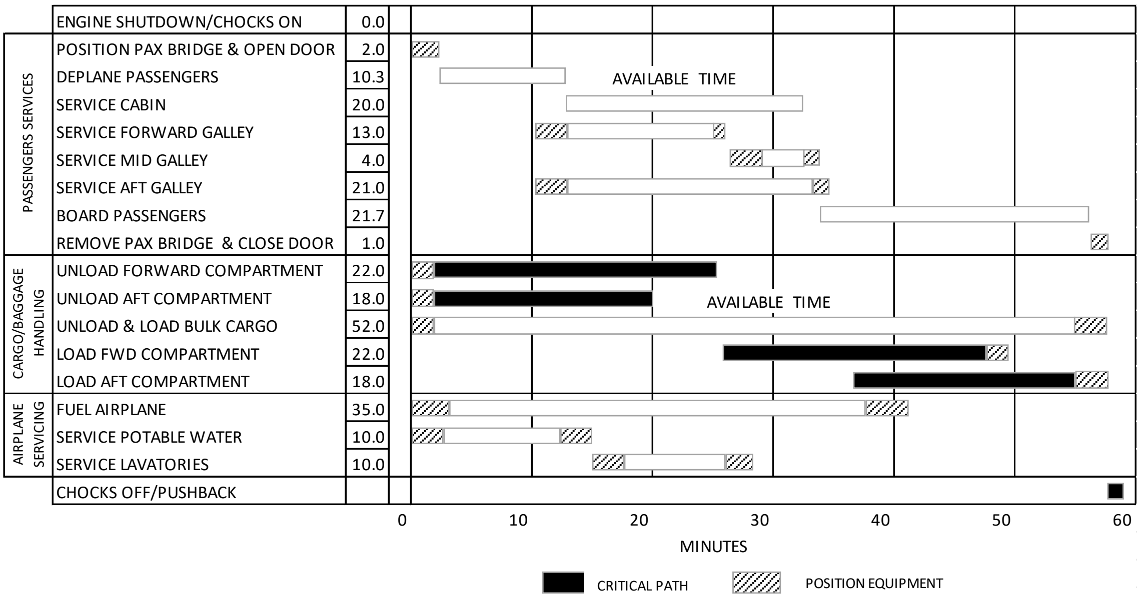


Figure 2. Turnaround processes for B787-10. Adapted from Boeing (2017).

Airlines plan the aircraft schedule time on the airport, between inbound and outbound flights, by considering [35]: (a) minimum recommended turnaround time [34], [36]; (b) route characteristics (e.g. point-to-point or hub-and-spoke network); (c) next destination (e.g. last flight, overnight parking and hub windows); (d) airport base type (e.g. full turnaround station or en-route station); (e) fleet optimization; (f) network accumulated delays and potential “slacks”; (g) slot allocation in coordinated airports; (h) crew availability; (i) minimum connecting time for passengers (e.g. hub and spoke strategies); (j) aircraft scheduled maintenance programs; and (k) the moment of the day (e.g. existence of long buffer times in the midday as a “fire break time” in order to control delay propagation in a network). Finding the optimal turnaround time is known as the Turnaround Time Allocation (TTA) problem [3], [37], [38]. This topic is related to airline scheduling [35], [39], airport slot distribution [40], [41], system congestion mitigation [21], [42], [43], resource allocation [33] and delay propagation [17], [44].

Airlines seek to increase fleet utilization by reducing total turnaround times; longer on-ground times between flights increases opportunity costs, as well as other expenses associated to the use of airport facilities [45]. However, if turnaround times are tightly scheduled, the airline can incur in local on-ground lateness, multiplying inherent inbound delays. This situation leads to reactionary delays and congestion problems. Moreover, a significant portion of delay generation occurs at airports, where aircraft connectivity acts as a key driver for delay propagation [46]. Apart from the associated economic costs for all involved stakeholders [47], delays have a substantial impact on the schedule adherence of airports and airlines, passenger experience, customer satisfaction and system reliability [3], [39], [48]. Therefore, uncertainty management and delay propagation affecting internal airport processes have received significant attention over the years [33], [49]–[53]. Increased on-ground periods through “buffers” and “fire break times” may act as delay recovery mechanisms, in order to control delay propagation in a network.

Therefore, the scheduling optimization problem for TTA (setting block times) is a trade-off between limiting the on-ground flight phase to the minimum required time (increasing fleet utilization and reducing airport parking associated costs) and adding an additional “buffer” time (allowing schedule adherence, absorbing inbound delay and ensuring crew and passenger connectivity).

Scheduled block time (SBT) setting is thus a crucial part in airlines’ scheduling [35], [48]. Two main approaches have been used to solve the TTA optimization problem. The first one considers a sequential view of the different processes that shape the aircraft turnaround, i.e. some tasks cannot be started until some others are completed [53]–[55]. This methodology distinguishes the required time for each partial operation, and the objective is to find the optimal order or the critical path that minimizes turnaround time by reducing costs. It leads to a version of the Resource Constraint Project Scheduling (RCPS) problem [56], an application of the Project Evaluation and Review Technique (PERT) method [53], [57], or a stochastic modeling followed by Monte Carlo simulation [49]. The second approach treats the turnaround process as a “single block”. In this case, the goal is to minimize costs considering the schedule adherence of flights. Costs results from delays (inherited from the previous flight and generated locally) or from adding an on-ground “buffer” (extra time - potential underused or untapped resources). This approach leads to mathematical optimization methods that evaluate the potential impact of schedule changes on flight delays and delay related costs [38], [58], [59]. Moreover, most of the proposed methods to solve the TTA problem can be categorized into two approaches, i.e., empirical/stochastic [49], [60]–[62] and numerical [38], [58].

The dynamically changing operation at airports makes it difficult to accurately predict operational times or generate fixed strategies for all situations [63]. Therefore, adaptive and stochastic approximation methods can be a useful tool for solving airport operational problems [37]. In the field of airport on-ground operations, optimal control theory and reinforcement learning methods have been previously applied for predictability and management of taxi-out and runway occupancy times [63]–[67]. These methods deal with the problem of finding a control law for a given system, such that a certain optimality criterion is achieved; the aim is to derive control policies.

Reinforcement learning and approximate dynamic programming methodologies have been proved to be effective for control of non-linear stochastic and dynamic systems [31]. This is aligned with the complex nature of airport operations and the uncertainties involved, which often make it difficult to obtain mathematical models to describe the complete airport dynamics. In such situations, feedback control techniques allow us to adapt the results to the changing conditions. Werbo’s work [68] illustrates the connection between various control theories and approximate dynamic programming.

Methodologically, we approach the TTA optimization problem from a dynamic management perspective, based on reinforcement learning. This allows us to develop a continuous adjustment of the optimal TTA policy through a feedback control system, in order to evaluate scheduling questions such as the variation of scheduled time and the efficiency of turnaround operations under different conditions (airline strategy, airport congestion, air traffic regulations and level of inbound delay). Therefore, when setting the optimal TTA, we consider not only outbound delay and “buffer” costs, but also the costs of (a) perturbations in schedule adherence, (b) internal (local) delays and (c) airport level of congestion.

Hence, the main contribution of the paper regarding the TTA problem is twofold: first, the introduction of a feedback control system approach, as a way to dynamically learn how to map situations to actions; and second, the consideration of additional costs, like those associated to system congestion and to the impact of schedule perturbations (availability of resources). This methodology that can be used to support decision making processes in balancing turnaround associated costs, improve departure time predictability (TOBT setting) and increase the system’s robustness.

3. Problem statement and methodology

Main opportunities to recover arrival delays and improve schedule adherence arise at the turnaround stage [11], [49], [69], [70]. For the purpose of this work, aircraft turnaround activities are aggregated as a “single” process or “black box”. This approach has proven its efficiency when assessing airline schedules and airport slot distribution [53]. It provides us with a “macro” view of aircraft turnaround operations and simplifies the observation and modelling work needed to adjust on-ground time allocation. To complete this approach we use a “timestamp” framework: the evolution of a flight, including the ground phase, can be described as a sequential flow of events [58], [71], [72]. Each of these events occurs consecutively, and if any of them gets delayed, this may result in subsequent processes also being delayed (unless certain “buffers” or “slacks” are added into the times allocated to the completion of certain tasks). The Airport Collaborative Decision Making (A-CDM) concept is based on the definition of "timestamps" to enable close monitoring of significant procedures. It aims at increasing the overall efficiency of airport operations by optimizing the use of resources and improving the predictability of events. The A-CDM framework focuses especially on aircraft turnaround and pre-departure sequencing processes [73]. The main contribution of this milestone approach is to achieve common situational awareness among all stakeholders by tracking the progress of a flight from initial planning to take-off. Regarding the aircraft turnaround time at an airport, the following timestamps and metrics are considered in the proposed methodology for the TTA problem [12], [73]:

- *SIBT (Scheduled In-Block Time)*: The time that an aircraft is scheduled to arrive at its first parking position.
- *SOBT (Scheduled Off-Block Time)*: The time that an aircraft is scheduled to depart from its parking position.
- *TOBT (Target Off-Block Time)*: The time that an aircraft operator/handling agent estimates that an aircraft will be ready, all doors closed, boarding bridge removed, push back vehicle present, ready to start up/push back immediately upon reception of clearance from the TWR (air traffic control tower).
- *AIBT (Actual In-Block Time)*: The time that an aircraft arrives in-blocks. Equivalent to Airline/Handler ATA (Actual Time of Arrival) and ACARS (Aircraft Communications Addressing and Reporting System) = IN.
- *AOBT (Actual Off-Block Time*): Time the aircraft pushes back/vacates the parking position. Equivalent to Airline/Handlers ATD (Actual Time of Departure) and ACARS = OUT.
- *MTT (Minimum Turnaround Time)*: Minimum time required to complete the turnaround process.
- *Turnaround "Buffer" (b)*: Increased on-ground period, i.e., schedule contingencies. There are two main categories of turnaround buffers [74]: (a) "at-gate buffer", defined as the additional time built into the schedule specifically to absorb delay whilst the aircraft is on the ground and to allow recovery between the rotations of aircraft (although it may be necessary to wait for connecting passengers or for a crew change), and (b) "slot buffer or slack time", due to the availability of airport slots: waits imposed upon the airline by factors that are essentially exogenous to its scheduling.
- *STT (SOBT-SIBT*): Scheduled Turnaround Time (MTT + b).
- *Arrival delay (AOBT-SIBT)*: d1, inbound delay. Inherited delays from previous flight segments are key elements for airlines when allocating the turnaround scheduled time. Reactionary delays (caused by late arrival of aircraft or crew from previous journeys) may accumulate their impact throughout the day due to network effects. This is why airlines often build in larger buffers on earlier legs, as these typically have greater operational impact [74]. Reactionary delays usually represent 40%-45% of all generated delay minutes [15], [75].
- *Turnaround delay: d2 (local delay) + d3 (ATFCM - Air Traffic Flow and Capacity Management delay)*. Local delay is due to perturbations in the system during turnaround operations (passenger and baggage processes, cargo, weather, airport facilities and procedures, technical and aircraft equipment, airline operations and handling), according to IATA delay coding system [7]. ATFCM delay is due to flow and capacity regulations: aircraft are hold on ground, preventing them to encounter airborne delays (holdings and/or path stretching) during which fuel is burnt and emissions are produced [76], [77].
- *ATT (AOBT-AIBT): Actual Turnaround Time (MTT + d2 + d3)*
- *Turnaround excess time: STT - ATT = [(d2+d3) - b]*. This concept shows that there is a difference between the aircraft scheduled turnaround time and the actual turnaround time that goes beyond operational delay. It is related to the idea that turnaround duration can be "artificially" enlarged by the presence of schedule "buffers" or ATFCM regulations.
- *Departure delay (AOBT-SOBT): d4, outbound delay*. Departure delays result from various reasons, such as "inherited" arrival lateness, delayed ground processes and/or disturbed ground operations.
- *Arrival congestion index (K)*: For each operation, K is the ratio of aircraft landed in the previous hour to the airport's declared arrival capacity at this hour. It ranges from zero to one for normal situations. Hence, K>1 indicates that the airport is operating in a congested state. Landing

airport capacity is the element of the network which causes congestion and potentially lengthy flight delays which spread over the network [50]. This index allows us to include in our optimization model not only airline schedules and delay costs, but also the airport level of congestion, as a precursor for far-reaching system-wide impacts.

The relationship between delays and operational times (scheduled, actual and targeted), is depicted in Figure 2.

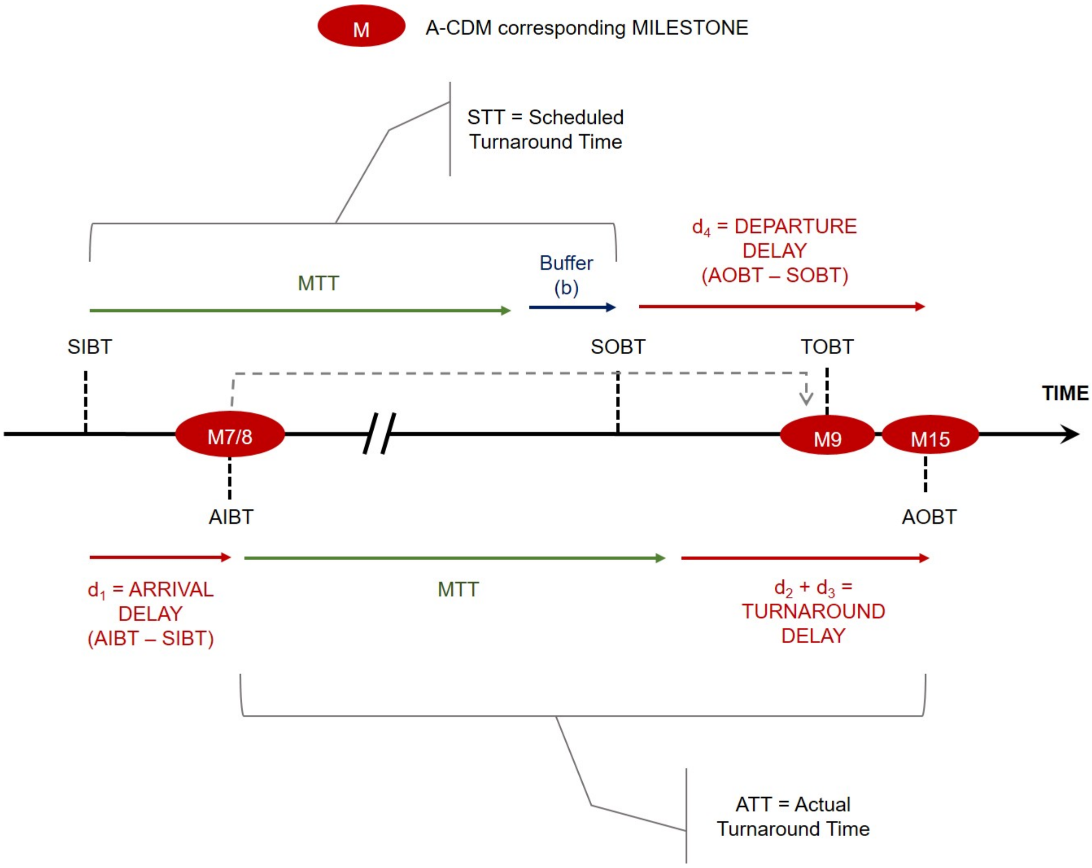


Figure 3. Milestones for the turnaround time allocation problem (not at scale).

Delays are defined as “schedule delays”: the difference between a planned time and the actual one. “Schedule delay” can refer to a difference in either the early or late direction [78]. Therefore, schedule delays can be positive or negative. Schedule delays are common occurrences in airline and airport operations, given the multiple agents involved, the stochastic nature of operating times, and the unexpected disruptions in tasks. “Negative” delays occur when the schedule is running close to plans and can cause issues for airport operations; e.g., disrupting the sequencing of flights and the allocation of resources (gates, handling equipment), especially during peak hours at busy airports [3]. “Positive” flight delays often cause significant problems for all the involved stakeholders; e.g., they affect operational and financial performance of airports and airlines, schedule adherence and use of resources, passenger experience and satisfaction, and system reliability [3], [45].

The problem we want to solve is stated as follows: given certain inbound delay and level of congestion (state variables), we seek to find the optimal turnaround time allocation (control law), by considering costs related to delays, congestion, schedule deviations and on-ground extra time. We use a hybrid approach between the classical empirical and numerical models: a dynamic management model through reinforcement learning, so a feedback control can be implemented. The use of congestion as a state variable allows us to include the impact of the time of day and the existence of potential “fire break times”; whereas the use of inbound delay considers the network effect (accumulated reactionary delays). These factors were found to be determinant in the TTA problem by previous studies [38], [49], [58].

We optimize the STT as a method for deriving global control policies. The STT is aggregated as a “single block” (including partial processes and on-ground “buffer”) so the methodology can be easily adapted to consider inherent factors (aircraft type, airport configuration, “buffer” strategies and handling operative characteristics) and external conditions (weather, air traffic regulations).

3.1 Dynamic management mathematical model

We consider the following non-linear discrete-time dynamic system

$$x_{t+1} = f(x_t, u_t), t = 0,1,2,\dots$$

with a continuous map $f : X \times U \to X$ on compact sets $X \subseteq \mathbb{R}^2$, $U \subseteq \mathbb{R}$. X is called the state space and U is the control space. Moreover, let us define the column vector $x_t = \begin{bmatrix} d_1 \\ k \end{bmatrix}_t$, where d_{1t} is a sequence $(t = 0,1,2,\dots)$ of arrival delays measured in minutes. On the other hand, k_t is also a time sequence containing the values of the arrival congestion index, concretely $0 < k_t \leq 1$. u_t is the turnaround time at time t. Additionally, we define a continuous *running cost* function : $X \times U \to \mathbb{R}$, such as $\pi(x_t, u_t; y)$, where y is a value that depends on external parameters. We assume π to be a bounded function with a lower limit.

Provided an initial state $x_0 = \begin{bmatrix} d_1 \\ k \end{bmatrix}_0$, our goal is to find a *feedback law* $F : X \to U$ that stabilizes the system, in the sense that discrete trajectories for the *closed-loop* system

$$x_{t+1} = f(x_t, F(x_t)), t = 0,1,2 \dots \tag{1}$$

minimizes the *accumulated cost*

$$\sum_{t=0}^{T-1} \beta^t \pi(x_t, F(x_t); y) \ , t = 0,1,2 \dots \tag{2}$$

where β is a discount factor, such as $0 < \beta < 1$. Moreover, y includes costs related to delays, congestion, schedule deviations and on-ground extra time, through $y = g(d_2, d_3, d_4)$, where g is a continuous function that assigns an input for the previous costs. d_2 is the local delay, d_3 is the ATFCM delay and d_4 is the outbound delay, measured in minutes.

In order to obtain the *feedback policy*, we use the following *optimality principle*

$$V(x) = \min_{u \in U} \{\pi(x, u; y) + \beta V(f(x, u))\} \ , x \in X, \tag{3}$$

Where $V : X \to \mathbb{R}$ is the optimal value function [see Bertsekas (1995)]. Using V, we find the *feedback map* by

$$F(x) \in arg \min_{u \in U} \{\pi(x, u; y) + \beta V(f(x, u))\} \ ,$$

whenever the minimum exists (under continuity of V, for instance). Let us define the *Bellman Operator* $T(\cdot)$ in equation (4), such as

$$TV(x) = \min_{u \in U} \{\pi(x, u; y) + \beta V(f(x, u))\}, \tag{4}$$

denoting by T^n the composition of the mapping T with itself *n* times, so

$$(T^{n+1} V_0)(x) = \min_{u \in U} \{\pi(x, u; y) + \beta (T^n V_0)(f(x, u))\}. \tag{5}$$

It can be proof [80] that $\lim_{n \to \infty} T^n V_0 = V^*$, by means of the contraction mapping theorem [see Bertsekas (1995)] where, operating in equation (5),

$$V^*(x) = \min_{u \in U} \{\pi(x, u; y) + \beta V^*(f(x, u))\} \ , x \in X, \tag{6}$$

being equation (6) a fixed-point equation to solve numerically [see Powell (2011)].

3.2 Reinforcement learning algorithm

The following reinforcement learning algorithm is designed in order to solve the fixed point equation (5). The idea for the algorithm comes from a wide range of literature related to this field [see Buşoniu, Schutter and Babuška (2010) for an excellent review]. In our case, we deal with a continuous-space and infinite-horizon problems. According to the literature, we have to deal with the intersection between Value iteration and Model-based techniques. We show the main steps of our algorithm, also involving approximate value iteration as a way to get a continuous-space solution from a discretized method [31], [81].

Below we present the main steps of the algorithm, which is based on repeatedly solving equation (1), based simultaneously on an estimate of $V(x)$. From an initial guess (for instance, $V^0(x)$), we approximate $V_i(f(x, u))$, and then an initial optimal candidate is obtained u^0 based on equation (3).

We get and optimal value $V^1(x)$ associated to u^0 and, in the same way, we get a new optimal candidate u^1. A sequence of fixed-points iterations continues until the sequence $\{V^1, V^2, \dots\}$ converges under the scheme defined in equation (5).

	Algorithm for Optimal Turnaround Managing
1	Define a set of *n* admissible values for d_1 and k such as $\widehat{x_i} = \{[d_1, k]_i\}_{i=1}^{n}$
	Formulate an initial guess for initial value $\widehat{v_i} = \{0\}_{i=1}^{n}$, usually zero.
	Initialize a set of *m* parameters to approximate the value function
	$\widehat{c_j} = \{0\}_{i=1}^{m}$, usually zero.
	Fix $tol > 0$ and β
2	**WHILE** $\epsilon > tol$
	Set $v_{old} = \hat{v}$
3	**FOR** $i = 1, \dots, n$
	Set y according to a cost rule
	$$v_{i,new} = \min_{u \in U} \left\{ \pi(\widehat{x_i}, u; y) + \beta v_i\left(\widehat{f(\widehat{x_i}, u)}\right) \right\}$$ $$v_i\left(f(\widehat{x_i}, u)\right) = \sum_{j=1}^{m} \hat{c}_j \, \varphi_j(f(\widehat{x_i}, u))$$
	END FOR
	Set $\hat{v} = v_{new}$
4	Get $\hat{c} = arg\min_{\mu} \|\hat{v} - \Phi(\hat{x})\mu\|^2$
5	$$\epsilon = \|v_{new} - v_{old}\|$$
	END WHILE

The notation used to approximate the value function (see step 3 in the algorithm) is:

1. v is a column vector of dimension n (corresponding to a discrete $V(x)$)
2. c is a column vector of dimension m
3. $\Phi(\hat{x})$ is a matrix $n \times m$ as follows $\Phi(\hat{x}) = \begin{bmatrix} \varphi_1(\widehat{x_1}) & \dots & \varphi_m(\widehat{x_1}) \\ \dots & \ddots & \dots \\ \varphi_1(\widehat{x_n}) & \dots & \varphi_m(\widehat{x_n}) \end{bmatrix}$
4. $\varphi_j(\widehat{x_i})$ is the j-esim basis function for the i-esim point [generally, a radial basis function, see Murray et al. (2002)].

We approximate the value according to the following learning model

$$v = \Phi(\hat{x})c + \varepsilon \tag{7}$$

Where ε is a random error (white noise).

The algorithm works as follows: in step (1), it starts with a set $\hat{x} \in X$ of possible values for the state variables (in this case, arrival delay and congestion), an initial value array $\hat{v}$ (generally zero) and an initial value for the set of parameters c. In (2), we iterate by minimizing the value function. At any algorithm step in (3), the cost π is computed. The target is to learn from the iterative mechanism in order to minimize the value by finding the best policies for u. In (4), at every step, the algorithm uses equation (7) to get the best fitting parameters to approximate the value function. An approximator for $v(f(\hat{x}, u))$ is needed because, in general, $x' = f(\hat{x}, u)$ are points out of the initially set defined in step (1), as we have applied $f(\cdot)$ to an optimal candidate to policy choice $u \in U$. This problem arises from the difficulty of working with a very fine discretization [due to the curse of dimensionality, see Powell (2011)] in the state space. Finally, when the algorithm converges in step (5) we have attained a set of optimal policies u^* (proposed turnaround times), linked to the initial state variables' points. We can approximate the optimal policy to any possible point in the state space.

The main key of our algorithm is that it reads from the intersection of the Bellman Equation, suitable for discrete-time Optimal control problems, the principle of approximate dynamic programming (ADP) [79] and some of the approaches of value iteration algorithms taken from the literature of reinforcement learning [84]. The approach of reinforcement learning used in this paper mainly deals with problems in which there is an agent in a data driven dynamic system. The agent makes some policy decisions regarding a set of control variables, so a reward is provided. But this policy also affects future rewards. When the optimum is reached, we obtain a feedback control law: the optimal policy is conditional to state variables (hence, it is a function, not only a value). One of the advantages of this technique is the possibility of the agent to readapt its policies in concordance with the possible sudden changes in the state variables, due to external shocks in the system. The way to synthetize a feedback policy from a data base is, firstly, to estimate a statistical time series model, mainly non-linear, that links the policy decisions to the state variables. We use a designed value iteration algorithm for this purpose. Hence, we adapt the cost functions to the airline characteristics and the previously estimated dynamic system. We also take advantage of mesh-free techniques in order to deal with the curse of dimensionality [81] and we apply ADP. One of the advantages of using ADP is that reduces the cost of computing (since we do not need, for instance, a rectangular mesh) and the amount of points needed to get the optimal value. Finally, we also apply Radial Basis Functions (RBF), very common in reinforcement learning literature [84], to approximate both the value function and the feedback policy at every point inside the continuous state space. The methodology for solving the TTA problem is illustrated in Figure 4.

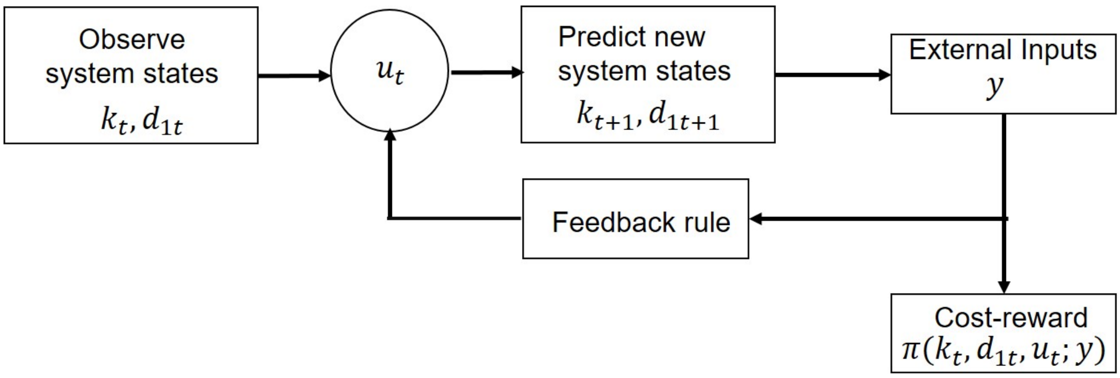
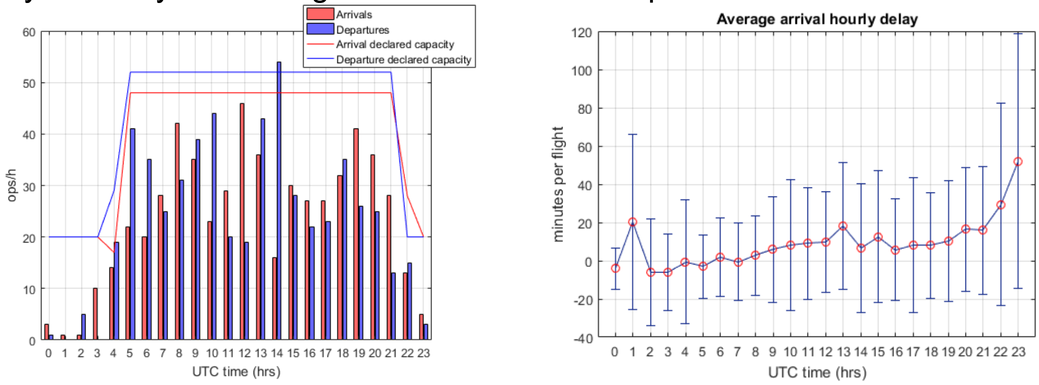


Figure 4. Functional block diagram for the methodology development

4. Case study

The TTA optimization problem is applied to a case study at Adolfo Suárez Madrid-Barajas Airport (LEMD). The observation period corresponds to July and August of 2016, when 67,678 aircraft movements (arrivals and departures) were registered at LEMD. Data regarding the aircraft and the flight (type, call sign/tail number and registration number) enable us to link the inbound and outbound movements, assessing each aircraft turnaround operation (i.e., trace the airport-airspace integrated operations). Therefore, by linking arriving and departing aircraft we can obtain the operational milestones and metrics for the TTA problem. The data preparation phase covers all activities required to arrange the final dataset from the initial raw operational data provided by the airport, including locating and refining erroneous measurements.

We perform an initial data analysis in order to understand the operational profile of turnaround operations at LEMD. Figure 5 (a) shows the demand profile against the declared capacity of the airport for the 22nd of July 2016 (a busy Friday with no significant disruptions in the network). Meanwhile, Figure 5 (b) illustrates the evolution of arrival average hourly delay over the day (with one standard deviation intervals), for the complete sample of operations. Arrival delay presents two peak periods (midday and late night), with higher levels at the end of the day. The operational analysis of the scenario shows that arrival delay increases and accumulates its impact over the day, due to the network effect. Therefore, a potential opportunity for delay recovering arises in turnaround operations.



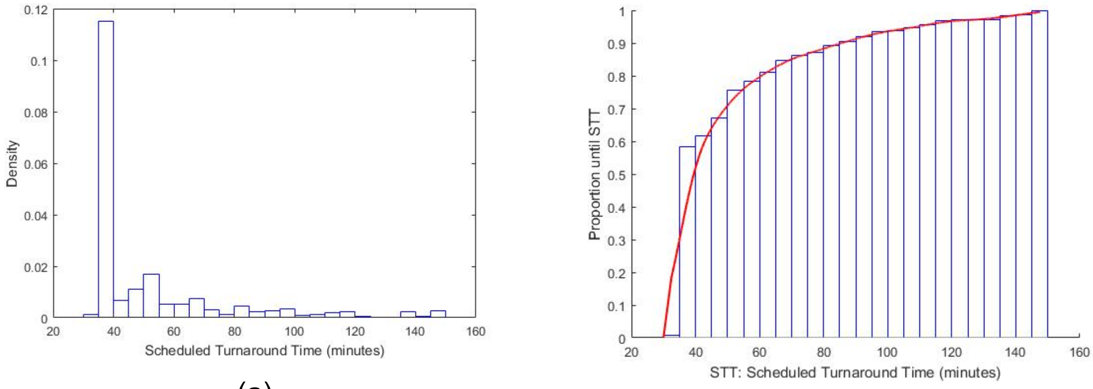
(a) (b)

Figure 5. (a) Traffic demand profile for the 22nd of July and (b) Evolution of average hourly arrival delay (min/op) throughout the day for the complete sample (the error bars denote one standard deviation intervals).

We analyse the turnaround operations of two airlines based on LEMD. The study is focussed on short-medium range routes (intra-European) with limited scheduled turnarounds (below 150 minutes). Therefore, no “parking” or overnight based aircraft are considered. Moreover, we appraise operations with medium-short delays (between -15 min and +40 min delay in arrival), since causes of short delays are often quite different from causes of long delays (drivers for long delays are more related to irregular operations than to operational inefficiencies) [15], [85].

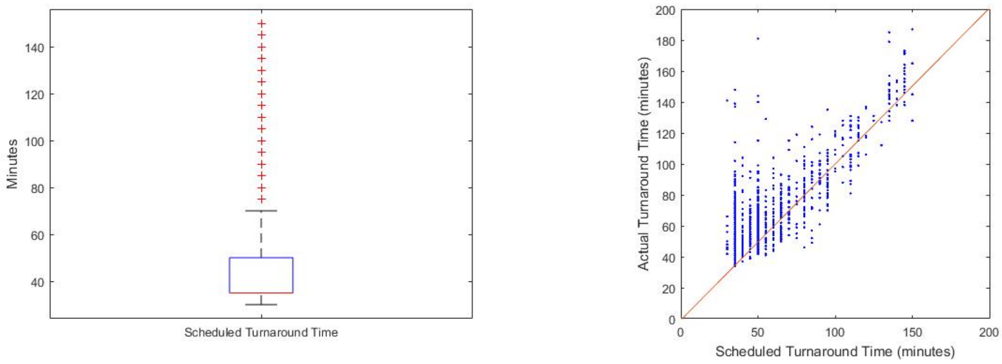
Each of the appraised airlines has a different business strategy. Airline A is a Low Cost Carrier with a point-to-point model. Meanwhile, Airline B follows a hub-and-spoke distribution system, with LEMD acting as its “central” hub (we therefore analyse the feeder traffic to long-haul flights). In order to obtain meaningful comparisons between the turnaround time allocation policies of both airlines, we select routes that are operated by similar aircraft in terms of on-ground service time (the Boeing 737 family and Airbus A319/A320/A321 models). We can obtain the minimum recommended turnaround time for each aircraft type and configuration from its Airplane Characteristics for Airport Planning manual [34], [36]. Therefore, we obtain a sample size of around 3,000 flights for each carrier (operated in the same season by similar aircrafts).

Figure 6 shows a statistical description of the turnaround process for Airline A (Low Cost Carrier) by depicting (a) the histogram and (b) the cumulative density function. Although the sample is rather heterogeneous (a range of 150 min), almost 80% of turnaround operations are scheduled to last less than 60 min. 58% of operations fall within the interval from zero to 40 min. The mean, median and mode for the turnaround’s scheduled length are 49 min, 35 min and 35 min respectively. Figure 7 (a) illustrate the boxplot for the scheduled turnaround time; the “sample outliers” (that could be due to faulty data or potential non-representative operations) might be excluded from the main sample, because of the possibility of biased results. Nevertheless, for a sample which is highly centred in the 35-45 interval with a wide range of variation, these outliers are important for the analysis, as they provide significant operational information. Figure 7 (b) represents the actual turnaround time (ATT) against the scheduled turnaround time (STT) for Airline A. Points below the diagonal line represent operations where the turnaround time has been compressed, by the use of buffers or improved ground operations efficiency or the allocation of more resources to speed up aircraft turnaround ($b > d_2 + d_3$). Meanwhile, points above the diagonal illustrate delayed turnaround processes ($b < d_2 + d_3$). Tighter scheduled turnarounds (lower values of STT), show a pattern of higher delayed operations.



(a) (b)

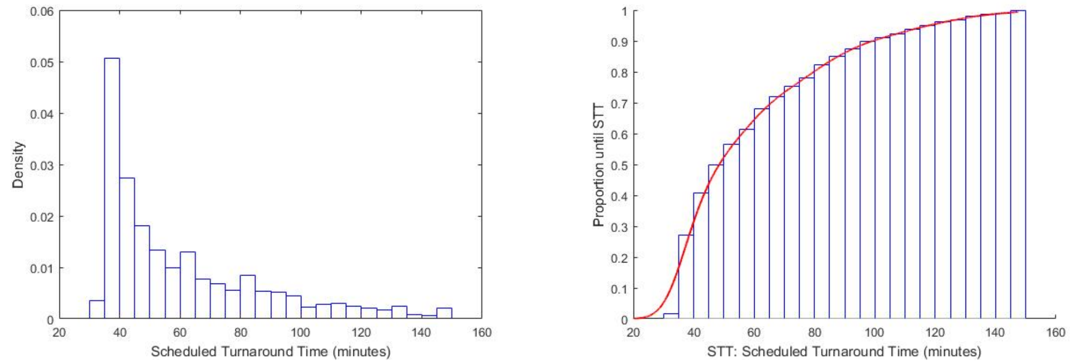
Figure 6. (a) Histogram and (b) Cumulative Density Function for the Scheduled Turnaround Time (min) for Airline A.



(a) (b)

Figure 7. (a) Boxplot for the Scheduled Turnaround Time (min) and (b) Actual Turnaround Time (min) against Scheduled Turnaround Time (min) for Airline A.

Figure 8 and Figure 9 illustrate a similar analysis of the turnaround process for Airline B (Network Carrier). The mean, median and mode for the turnaround's scheduled length are now 58 min, 50 min and 35 min respectively. Data shows a higher dispersion in the STT of the Network Carrier; approximately 60% of turnaround operations are scheduled to last less than 60 min and 27% of operations fall within the interval from zero to 40 min. Hence, for similar routes and aircraft models, the Low Cost Carrier tends to schedule tighter turnarounds (in the purse of high daily aircraft utilization). Moreover, Figure 9 (b) illustrates that points above and below the diagonal ("positive" and "negative" turnaround excess times) are more equally distributed than in Figure 7 (b).



(a) (b)

Figure 8. (a) Histogram and (b) Cumulative Density Function for the Scheduled Turnaround Time (min) for Airline B.

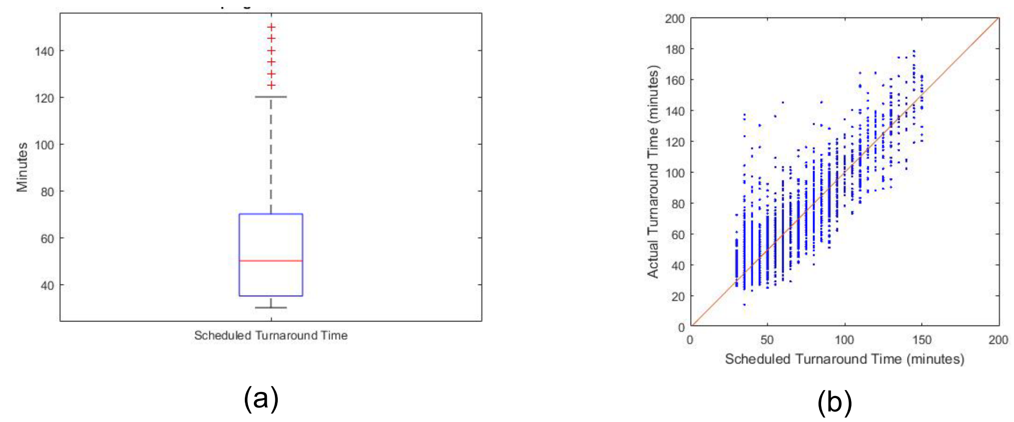


Figure 9. (a) Boxplot for the Scheduled Turnaround Time (min) and (b) Actual Turnaround Time (min) against Scheduled Turnaround Time (min) for Airline B.

Figure 10 illustrate the arrival delay histogram for (a) Airline A and (b) Airline B. Data show that in the group of considered delays (-15 min < d1 < 40 min), the Low Cost Carrier presents a "skewed left" distribution: the tail of "negative" delays is considerable longer. For the Network Carrier, are more symmetrically distributed.

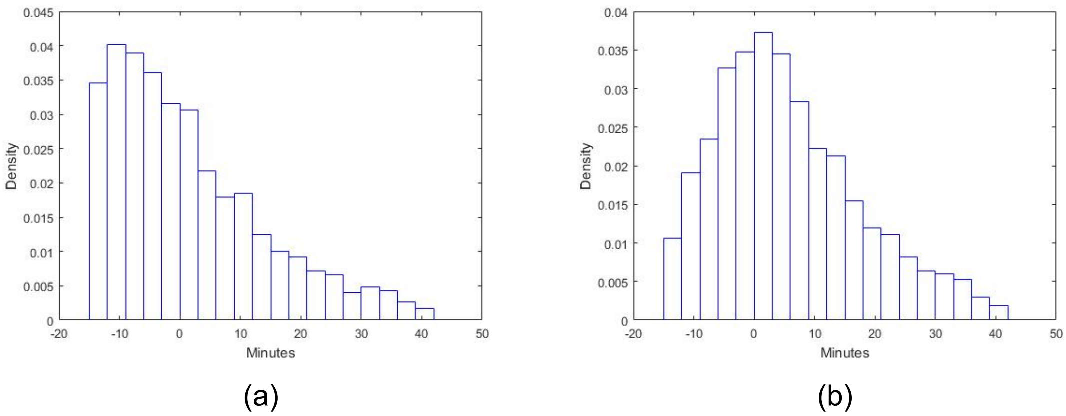


Figure 10. Arrival delay (min) histogram for (a) Airline A and (b) Airline B.

Some arriving delayed flights might propagate this delay to their subsequent departure leg (reactionary delay). In order to model this propagation effect, and asses the optimal turnaround time allocation, the scheduled turnaround times (STT) and the minimum time required to perform the turnaround operation (MTT) are computed for each flight. STT is obtained from the airport operational data by linking inbound and outbound flights. Meanwhile, MTT is estimated based on the aircraft type as follows. Figure 6 (b) and Figure 8 (b) provide the turnaround Cumulative Density Function (CDF) for the scheduled turnaround times of both airlines. For airline B, the MTT has then been computed for each individual flight as a random value between the 10% and the 50% interval of the probability distribution. Note that if this MTT is lower than the STT, then the MTT has been considered to be the STT. Montlaur and Delgado (2017) already found this procedure to be efficient when analyzing the MTT. For airline A, where 58% of operations fall within the interval from zero to 40 min, MTT for each aircraft type is obtained by comparing the minimum recommended turnaround time (at the Airplane Characteristics for Airport Planning manual) with the scheduled and actual turnaround time for each operation.

5. Results and discussion

This section shows how a novel machine learning approach is used for the TTA problem, illustrating the main results.

5.1 Models and estimated functions

We estimate a set of models corresponding to the discrete-time dynamic systems related to equation (1). Considering equally spaced time gaps in the data generating process, we estimate discrete-time series models [86] following an iterative methodology, in order to find the best specification under our sample conditions.

Regarding the state variables, we find as best models a logarithmic one for the arrival congestion index (k) and a linear-log for the arrival delay (d_1). The functional form of the estimated equations is as follows

$$log(k_t) = \beta_0 + \beta_1 \log(k_{t-1}) + \beta_2 d_{1,t-1} + \beta_3 \log(u_t) + \beta_4 \log(u_t) \times \log(k_{t-1}) + \beta_5 \log(u_t) \times d_{1,t-1} + \epsilon_t$$

$$d_t = \delta_0 + \delta_1 \log(k_{t-1}) + \delta_2 d_{1,t-1} + \delta_3 \log(u_t) + \delta_4 \log(u_t) \times \log(k_{t-1}) + \delta_5 \log(u_t) \times d_{1,t-1} + a_t$$

Where ϵ_t and a_t are uncorrelated, independently and identically distributed white noise processes. The parameters are estimated by Least Squares (see Table 1) where we show the best fitting alternatives.

Table 1. Parameters for the model

	Airline A		Airline B	
VARIABLES	$\log(k)$	d_1	$\log(k)$	d_1
$\log(k_{t-1})$	0.188***	69.06***	0.947***	2.984**
	(0.0651)	(8.443)	(0.0657)	(0.819)
$d_{1,t-1}$	0.00324***	-0.265***	-0.000337	0.120*
	(0.000606)	(0.0786)	(0.000616)	(0.0152)
$\log(u)$	0.0561***	-3.388***	-0.0134	4.366***
	(0.00894)	(1.159)	(0.00903)	(1.102)
$\log(u) \times \log(k_{t-1})$	0.105***	-17.08***	-0.0494***	1.113**
	(0.0149)	(1.934)	(0.0156)	(0.402)
$\log(u) \times d_{1,t-1}$	-0.000738***	0.0771***	7.54e-05	0.00496
	(0.000136)	(0.0176)	(0.000143)	(0.0174)
Constant	-0.469***	15.37***	-0.0801**	-6.328
	(0.0415)	(5.379)	(0.0387)	(4.728)
Observations	2,990	2,990	3,892	3,892
R-squared	0.613	0.680	0.757	0.748

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The parameters shown in Table 1 are used to feed the algorithm for turnaround managing in step (2).

For the model total cost function we consider the costs associated to: (a) departure delay (d_4), (b) "buffer" extra time on-ground, (c) perturbations in schedule adherence, (d) local and ATFCM delays (d_2 + d_3) and (c) airport level of congestion. The internal parameters of the cost function shape the sensitivity of the system to these perturbations and are modelled using past studies [3], [38], [47], [64].

5.2 Policy results

We run our algorithm considering a discount parameter of $\beta = 0.95$, similar to the one used in the literature [63], [64]. The main outcome of the algorithm is the feedback map displayed on Figure 11 and Figure 12. The optimal turnaround policy time is a function of both state variables: arrival congestion index (k) and arrival delay (d_1). The numerical solutions of the method allow airlines to obtain policy recommendations.

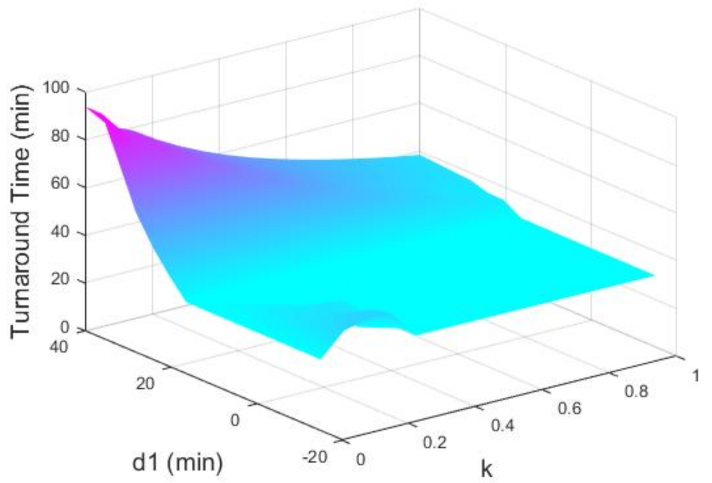


Figure 11. Optimal turnaround time allocation policy for Airline A (Low Cost Carrier).

For Airline A (Low Cost Carrier), “negative” inbound delays with low levels of arrival congestion (below 0.2) provide an optimal policy for turnaround times that is slightly above the minimum turnaround time (MTT). The optimal policy is highly influenced by arrival delays: turnaround time grows with d_1 at a significant rate when d_1 is in the interval between 20 and 40 minutes (aiming to absorb inbound delays on the ground). Nevertheless, for this range, congestion indexes greater than 0.2 considerably reduce the optimal policy (the costs of extra on-ground time and induced system congestion limit the enlargement of the turnaround time).

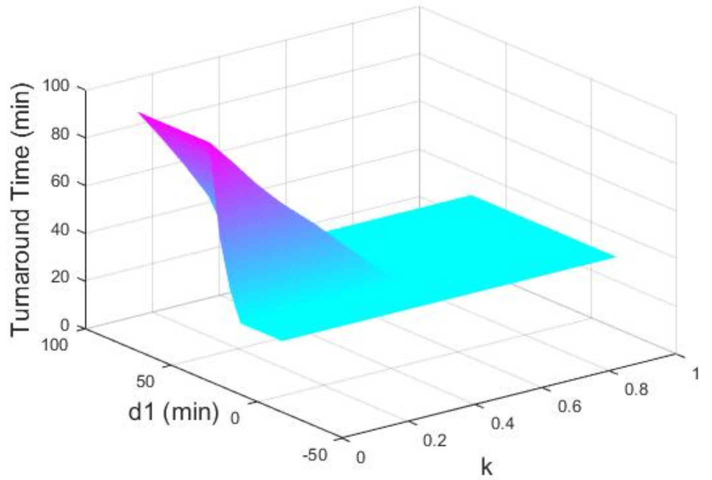


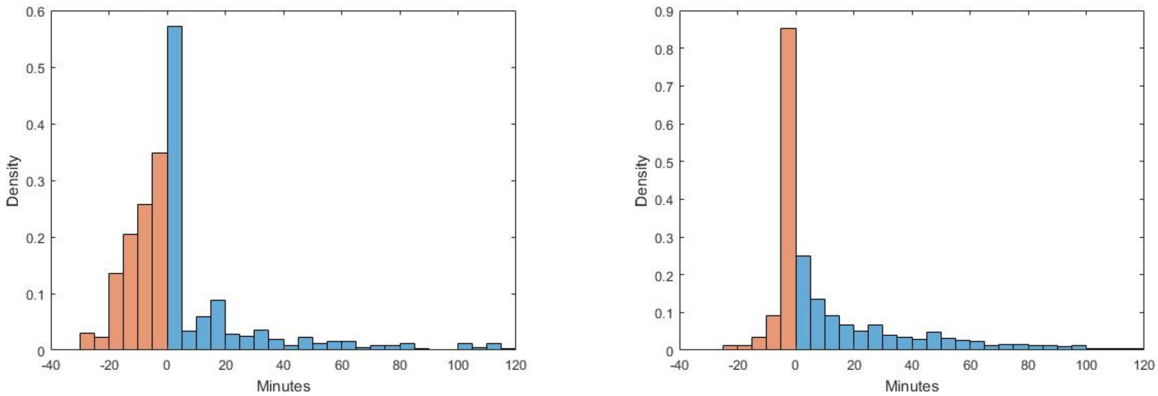
Figure 12. Optimal turnaround time allocation policy for Airline B (Network Carrier)

For Airline B (Network Carrier), the optimal turnaround time is almost always set in the MTT, especially with high values of the congestion index (driven by the high costs related to losing connectivity of the feeder traffic during the hub windows -highly congested periods-). However, there is area defined by arrival delays between 20 and 80 minutes and congestion indexes between zero and 0.2 where the optimal turnaround time abruptly grows with d_1. Congestion indexes between 0.2 and 0.4 limit the growth of the optimal policy with d_1. k affects the turnaround time in a discrete way: certain ranges of k have an impact on the optimal policy, but it is not a monotonous effect as in the case of d_1, where marginal changes in the variable clearly affect the objective.

Results regarding turnaround time allocation are in line with those obtained by previous studies: punctuality performance of inbound aircraft highly influences the optimal turnaround policy [49], [58]. This conclusion is especially significant for Low Cost Carriers. Likewise, results concerning the impact of congestion on turnaround processes are aligned with the conclusions of previous studies: during highly congested periods, limiting scheduled "buffer" times on the ground reduces the cost of system saturation [42], [64], [71].

5.3 Comparison between recommended and real decisions

Figure 13 illustrates the histograms that represent the distribution of the difference between the real policy decisions (obtained from the historical data) versus the optimal recommendations of the model (obtained by applying the values of the state variables recorded at the database to the feedback decision rule). In both cases the distributions are centered in zero. Even so, we find different patterns regarding the optimal policy. For Airline A [Figure 13 (a)], although there is a high quantity of probability accumulated around zero, we can observe that this carrier uses to unbalance its policy with more probability in negative values (the turnaround time is "underprovided"; i.e., they are scheduling tight turnaround times). Therefore, their real policies are, generally, slightly needing more time to achieve the recommended optimal turnaround time. However, the distribution is also skewed to the right, which means that there are some extreme points (in which their scheduled turnaround time is remarkably greater than the optimal policy). In the case of Airline B [Figure 13 (b)], the distribution also has a tendency to be right skewed. But, in general, their probability is more concentrated around zero, which means that their planned turnaround time is closer to the optimum one.



(a) (b)

Figure 13. Distribution of the difference (min) between the real policy decision and the recommended one for (a) Airline A and (b) Airline B.

6. Conclusions

Turnaround time allocation models usually consider static and fixed strategies. The optimization methodology developed in this paper improve the traditional view by considering a feedback control technique based on a reinforcement learning approach. Therefore, the model is capable to adapt the proposed policy to changes in the system. This is particularly important for airline scheduling problems: the stochastic characteristics of airline operations make them dependent on their strategy and procedures, but also on the operating environment (airport and air traffic regulations). Furthermore, the nature of the airline business model (more connecting traffic or more point-to-point traffic) and the schedule planning (the usage of "buffer" time) are key elements when managing on-ground operations, and the proposed method is capable to adapt the results to the airline sensitivity to external factors. Moreover, traditional turnaround management methods focus their analysis only on delay and "buffer" costs. Our model widens this approach to a system-level solution by also considering cost related to perturbations in schedule adherence, local and ATFCM delays and airport level of congestion.

Results show that an accurate use of turnaround time allocation methods (through schedule "buffer" time) is able to manage the punctuality performance of turnaround aircraft by minimizing system costs. The influence of arrival punctuality of inbound aircraft is found to be significant on the departure punctuality of aircraft. This is particularly important for Low Cost Carriers, as these airlines tend to schedule tighter turnaround. The level of congestion is also a key element when assessing an optimal turnaround policy. This is remarkable for Network Carriers, as they tend to operate during highly congested hub windows and have the risk of losing connectivity of the feeder traffic. Regarding the analysis of real turnaround policies, the appraised Low Cost Carrier tends to schedule "underprovided" turnaround times, while the Network Carrier plans turnaround times closer to the optimum ones. The scheduling of turnaround time is driven by the airline business model and should consider the individual punctuality performance of each route and airline; i.e. different schedule "buffer" times should be applied depending of the particular characteristics of the route, the airline and the airport.

The proposed method has two main applications: (a) from a planning point of view, it allows us to obtain optimal policies that react to the state variables (i.e., we provide a decision-making rule and not only a static optimal value); and (b) from a post-analysis perspective, the methodology allows us to appraise past strategies, by comparing the real decisions to the optimal solutions proposed.

Machine learning techniques, particularly reinforcement learning, has proven to be an excellent method to solve the turnaround time allocation problem. It may help airlines to reach schedule adherence, absorb inbound delay, ensure crew and passenger connectivity and improve operational predictability for departure times.

Future work will be focused on improving the accuracy and reliability of the model (more complete testing data and methodological improvements), and on comparing the results when the methodology is applied to other airline and airports (generalize the case study, particularly regarding the cost function and the functional form of the state variables).

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8. Copyright Statement

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