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USING SIMULATION TO ESTIMATE CRITICAL PATHS AND SURVIVAL FUNCTIONS IN AIRCRAFT TURNAROUND PROCESSES

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ABSTRACT

In the context of aircraft turnaround processes, this paper illustrates how simulation can be used not only to analyze critical activities and paths, but also to generate the associated survival functions – thus providing the probabilities that the turnaround can be completed before a series of target times. After motivating the relevance of the topic for both airlines and airports, the paper reviews some related work and proposes the use of Monte Carlo simulation to obtain the critical paths of the turnaround process and generate the associated survival function. This analysis is performed assuming stochastic completion times for each activity in the process – which contrast with current practices in which deterministic times are usually assumed. A series of numerical experiments considering the Boeing 737-800 aircraft are carried out. Different levels of passengers' occupancy are analyzed, as well as two alternative designs for the turnaround stage.

1 INTRODUCTION

With the continuous increase in the number of passengers and the emergence of low-cost companies, the commercial aviation sector has become a highly competitive one. Thus, airlines need to operate as efficiently as possible in order to make a profit. It is estimated that the number of passengers will grow at around 5% a year during the next 20 years. This scenario will result in a deficit of capacity at airports. To improve their capacity, airport managers need to find ways to operate their infrastructures and services as efficiently as possible, as well as to invest in building new infrastructures.

The aircraft turnaround stage is one of the most critical processes that airlines and airports have to face in their daily operations. The turnaround of an aircraft comprises all tasks that need to be completed since it arrives to the assigned gate until it is ready for departure (Figure 1). These activities include: boarding and disembarking passengers, cabin-cleaning and catering, aircraft maintenance and re-fueling, loading and unloading of baggage and cargo, security checks, etc. According to Eurocontrol (http://www.eurocontrol.int), during 2015 the average delay per flight was about 9.3 minutes. Almost 45% of these delays were due to late arrivals of aircrafts, passengers, crew, or cargo. Also, about 30% of these delays were attributed to the airline itself. Some of these delays are strongly correlated with the turnaround process. Notice that whenever an aircraft is waiting at the airport, additional costs are generated for the airline in terms of passengers' dissatisfaction (Fricke and Schultz 2009). According to a study conducted at the University of Westminster (Cook, Tanner, and Anderson 2004), each minute of delay costs to the airline about 25 euros. This might seem a low quantity, but when multiplied by the number of flights a year that a company operates, it becomes an important source of cost. Therefore, it is in the interest of the airlines to minimize their turnaround times. Likewise, as previously discussed, this is a shared goal with airport managers, since it allows increasing the airport capacity to manage flights.

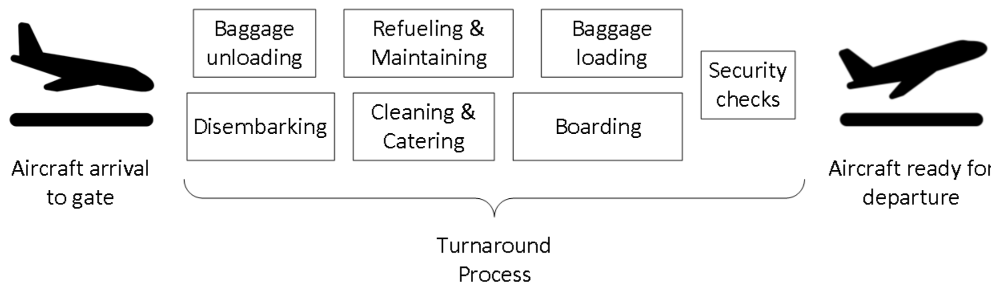

Figure 1: Typical tasks in an aircraft turnaround process.

One of the characteristic features of the turnaround process is that, while some activities can only be developed sequentially – e.g., you cannot begin to board passengers until the disembarking and cleaning processes are completed –, there are certain tasks that can be developed in parallel – e.g., passengers' boarding and baggage loading. In most studies, completion times associated with each task are considered to be deterministic, while in real-life they have a stochastic nature. Accordingly, one of the main motivations of this work is to analyze the turnaround process considering stochastic times for each task, thus studying how the introduction of random times affect the critical paths (sequences of tasks) to be completed, as well as the survival function of the process, i.e., the function that determines the probability that the turnaround stage will be finished in any future target-time. In order to perform such an analysis, a simulation-based approach is introduced.

The remaining sections of this paper are structured as follows: Section 2 provides details of the particular problem addressed in this paper. Section 3 reviews related work in the literature. Section 4 gives an overview of the proposed simulation-based approach and how it integrates survival analysis concepts. A series of computational experiments are described in Section 5, and some insights are analyzed in Section 6. Finally, Section 7 summarizes the highlights of this paper and proposes some future research lines related to the extension of the approach into a simheuristic algorithm (Juan et al. 2015).

2 THE AIRCRAFT TURNAROUND PROCESS

Aircraft turnaround is the orderly process of all the activities carried out on the aircraft since it arrives to its assigned gate until it is ready for departure. Some of these activities can be developed in parallel, while others have to be completed following a sequential path. Thus, for example, disembarking, cabin cleaning, and boarding of passengers are sequential activities, while baggage loading and passengers boarding can be done in parallel. Turnaround times are not the same for all flights, since they depend upon several factors. Thus, for instance, the length of the flight is essential when planning the turnaround time. If the flight is a long distance one, the turnaround time will typically be greater, since it usually affects a large-size aircraft. The type of flight is also relevant when planning the turnaround: often, an international flight where customs and immigration controls are requested might require longer turnaround times than domestic flights. The type of airline must also be taken into account: low-cost airlines tend to perform just the strictly necessary tasks, since its main objective is to minimize costs – including turnaround times. For example, on certain low-cost flights it is possible that catering operations are not required. On the other hand, traditional companies – who are looking for a greater customer's satisfaction – might perform longer turnaround processes with complementary activities.

The main activities related to the turnaround process are represented in Figure 2 (Wu 2012): *(i)* passengers' boarding / disembarking, either if the aircraft is located in a remote stand or adjacent to a finger; *(ii)* luggage loading / unloading, either if bulk containers are used or not; *(iii)* refueling, which is only allowed if certain security conditions are satisfied; *(iv)* routine maintenance, i.e., tasks related to a basic verification of the aircraft conditions to start a new flight; *(v)* catering loading / unloading, if any; *(vi)* cabin cleaning, which is carried out in the time period between passengers' de-boarding and the subsequent boarding; *(vii)* security procedures, which refer to certain checks that must be carried out to ensure the proper functioning of the aircraft systems – e.g., checking of the evacuation ramps, oxygen masks, fire-prevention systems, etc.; and *(viii)* preflight checklist, which refers to verify the proper functioning of all the basic flight systems in the aircraft – this task is carried out once the boarding has finished and before starting the takeoff operations.

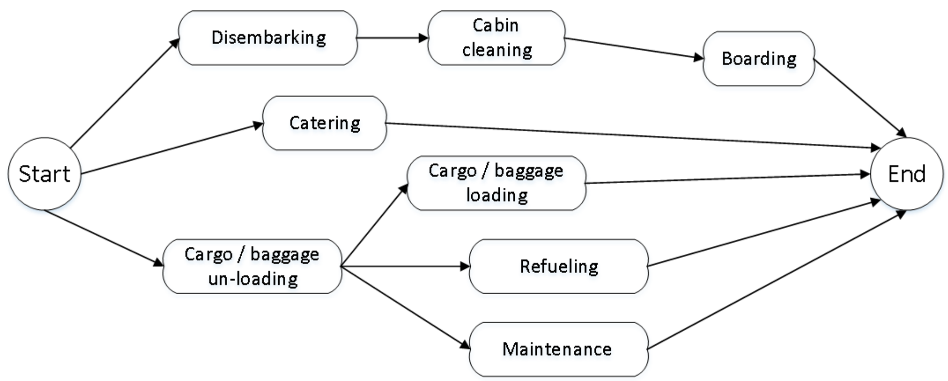

Figure 2: Graph representation of a turnaround process.

3 RELATED WORK

In the scientific literature, there are two main approaches for analyzing aircraft turnaround processes. In the 'task-based' approach each activity is individually analyzed considering its completion time and how it contributes to the completion time of the entire stage. By analyzing these individual activities, managers can identify critical paths and propose policies to reduce potential bottlenecks. On the contrary, in the 'aggregated' approach no details on the activities are provided. Instead, the main goal is to decide about the size of a buffer time that can be allocated in order to optimize the trade-off between delay costs – generated by unexpected delays in the turnaround stage – and the cost of keeping the aircraft at the airport during more time than necessary (Fricke and Schultz 2009, Wu and Caves 2004).

In this paper we focus in the task-based approach, where turnaround activities are typically analyzed using the classical project evaluation and review technique (PERT). The use of this technique has two correlated objectives: firstly, to assess and improve the efficiency of the operational processes carried out by the airline; secondly, to assess and improve the efficiency of the allocation of human resources (Wu and Caves 2003). Figure 2 shows a representation of a classical turnaround process, in which we can distinguish up to five paths. One of the goals of our approach is to determine which of them has more probabilities to be the critical one (i.e., the one requiring more time to be completed) as well as how random delays in any of them will affect the random completion time of the entire stage.

In most of the studies carried out in the literature, completion times associated to each activity are considered to be a single deterministic value (i.e., the expected time). In order to introduce a more realistic version, some authors propose to consider three possible (yet still deterministic) times for each activity (Wu 2012): *(i)* an optimistic completion time; *(ii)* an 'average' completion time; and *(iii)* a pessimistic completion time.

Also, some authors propose the use of Markov Chains to simulate the dynamic and stochastic behavior of the different turnaround activities (Wu and Caves 2004). The corresponding model is applied to two sequential streams of critical activities: 'cargo and baggage handling' and 'cabin cleaning and passenger processing'. For each of the streams their main states and potential disturbances are defined. Probability distributions, such as the Exponential, Beta, and Normal are used for modeling of the completion times of each activity – this, in our view, is a conceptual mistake probably imposed by the method employed, since it would be much convenient to use Weibull or lognormal probability distributions for modeling non-negative random times. In addition, four independent events causing frequently delays in the turnaround process are added to the model: a fueling delay, a delay while switching aircrafts, a delay due to a damaged aircraft, and a delay in maintenance checks. The model is offered to airlines as a tool to explore their turnaround processes and their potential bottlenecks.

Yet, other authors propose to model the problem as an extended resource-constrained project scheduling problem (x-RCPSP) (Kuster, Jannach, and Friedrich 2009). The x-RCPSP is based on the definition of alternative activities, i.e., different ways to perform the same activity in a faster way by allocating additional resources to it. Thus, for example, an alternative activity for the disembarking of passengers using only one door would be to do it using two doors (although the cost would be higher, the completion time would be significantly reduced in most cases). The idea behind the x-RCPSP is to offer managers the possibility of dynamically adapting their decisions in response to unexpected events, e.g., if an aircraft arrives late at the boarding gate, the manager can decide to use alternative activities that will reduce the effect of accumulated delays.

Another interesting concept is the 'ground manager' one, which is introduced in the context of collaborative decision making with the aim of minimizing the turnaround time (Oreschko et al. 2012). Three main assumptions are made: *(i)* the turnaround stage can be modeled as a stochastic process; *(ii)* its duration depends on various parameters, including: type of airport, number of passengers, type of airline, etc.; and *(iii)* arrival delays have an important influence on the completion time of each task, as well as on the occurrence of interactions among tasks. Their model is also based on the concept of critical path. These authors model the activities' completion times using a Weibull probability distribution, which is probably the most appropriate distribution for modeling non-negative completion times. Similar to Wu and Caves (2004), the authors use this model to predict the turnaround completion time based on that of the critical path. They increase the accuracy of their prediction as more variables are known to the problem moving from strategic to operational level. However, the authors do not evaluate the probability of completing or not the turnaround process within the scheduled time. Hence, it is up to the decision maker to evaluate this risk during the planning phase. In contrast with previous works, our approach provides decision makers with a useful tool to perform a risk analysis of turnaround operations, both for the entire process and for individual activity paths.

4 COMBINING SIMULATION WITH SURVIVAL ANALYSIS CONCEPTS

Several authors have studied in detail different ways of combining Monte Carlo as well as discrete-event simulation with survival analysis (Faulin et al. 2010). As suggested in some of these previous works, it will be assumed that the completion time associated with each task can be modeled as a random variable. These random variables will follow a series of given probability distributions – most likely, a Weibull or a lognormal probability distribution (Faulin et al. 2008). Then, in order to analyze the probabilistic behavior of the turnaround process we are interested in estimating its associated survival function, i.e., the function that determines the probability that the process is still 'alive' (not finished) at any target time in the future. Given a fixed target time $t_i \geq 0$, our goal is to estimate the probability that the turnaround process will still be 'alive' (not completed) at t_i. In our case, the process will still be alive as far as any of the different paths of activities is not completed yet. In other words, the turnaround process will be completed as soon as all the mandatory paths are terminated. The status of the process at any given time can be then considered as a Bernoulli random variable (either finished or not), and the previously described probability can be estimated by using Monte Carlo simulation and computing the ratio between the number of times that the process is still operative at t_i and the number of simulation runs. Of course, confidence intervals for these estimates can also be obtained (Juan and Vila 2002).

Being able to compute the survival function associated to a turnaround design might provide interesting insights for the decision maker. For instance, it might be the case that alternative feasible designs (i.e., different combinations of paths satisfying the order constraints) might generate different survival functions with varying probabilistic behavior – even if they have similar expected completion times. Thus, Figure 3 shows the survival functions associated with two different turnaround designs. Notice that for target times lower than t_1 (e.g., t_0), design B seems to outperform design A, i.e., the probability of the turnaround being completed by t_0 is higher with design B. On the contrary, for target times higher than t_1 (e.g., t_2), design B shows a higher probability that the turnaround process is still not terminated yet – and, therefore, design A should be preferred instead. This analysis might be specially interesting when the manager has to face a predefined deadline for the turnaround stage that must be satisfied.

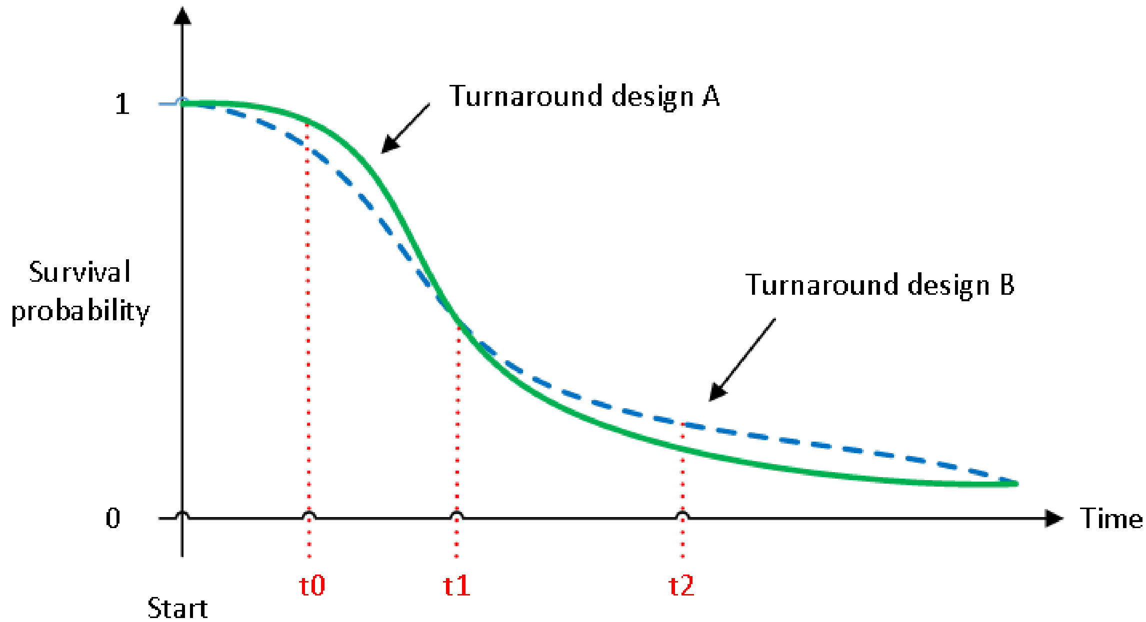

Figure 3: Comparison of two crossing survival functions of different designs.

Notice that simulation can not only provide estimates of the survival function at each target time, but it can also provide detailed information on the process, such as: observations on the random completion times associated with each path, percentage of times each of the paths has been acting as a bottleneck, and observations on the random completion times associated with the entire turnaround process, from which useful statistics – such as average times, variance, and quartiles – can be easily computed.

5 NUMERICAL EXPERIMENTS

A series of experiments have been carried out to test our simulation-survival approach. These experiments refer to turnaround processes associated with a Boeing 737-800. The turnaround activities are the ones proposed by the aircraft manufacturer, which assume deterministic times (Figure 4). The graph representation of this example is the previous one given in Figure 2.

In order to provide more realism to our analysis, we employ Weibull probability distributions (considering the aforementioned deterministic values as expected values) to model the completion times of each activity. Finally, we have also analyzed the performance of the turnaround process under three different levels of passengers' occupation (75%, 90%, and 100%), since working under different levels of occupation could generate variations in the critical path and the associated survival functions.

According to the activities proposed by Boeing, three main types of activities can be observed: the activities carried out in the cabin, the handling activities, and the ones associated with servicing the aircraft.

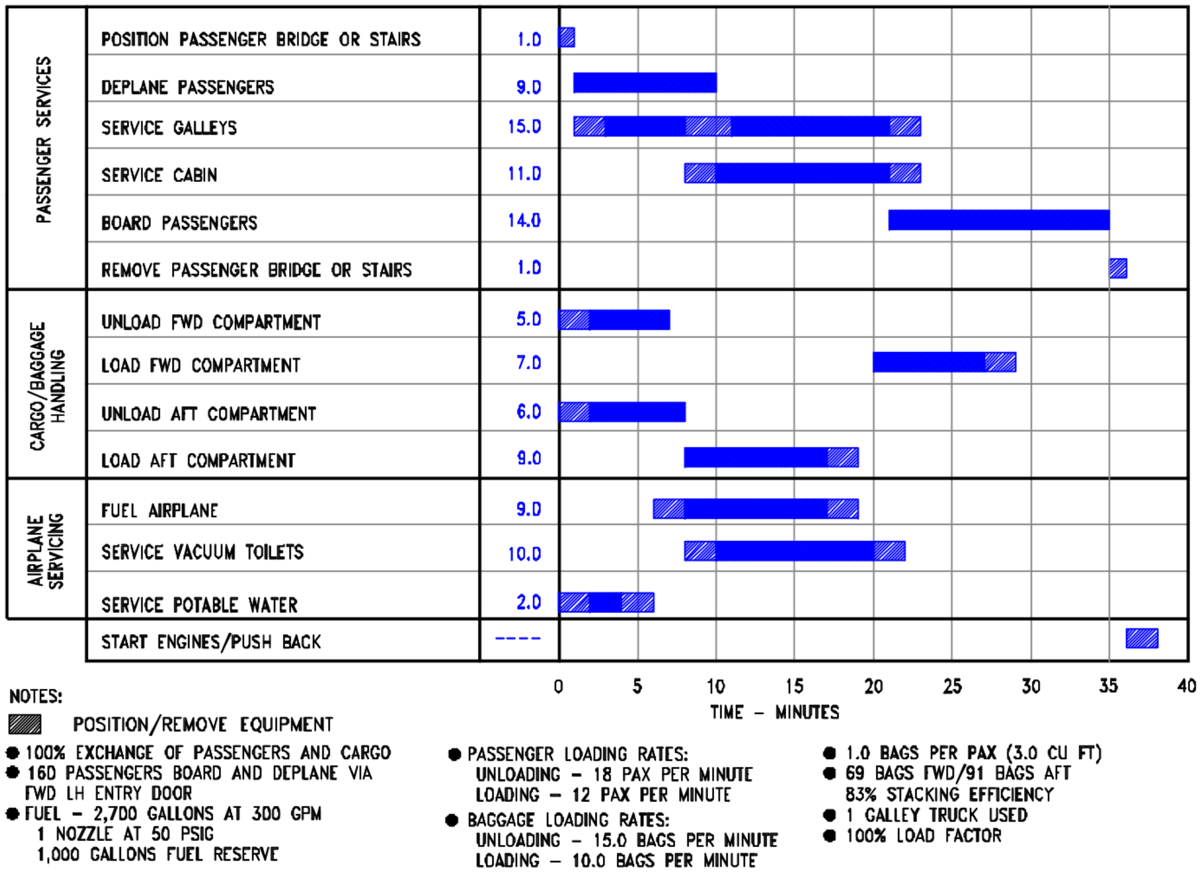

Figure 4: Standard turnaround activities for the Boeing 737-800.

Table 1 shows the estimated average times for each turnaround activity for the B737-800. It also shows times taking into account the different passenger-occupancy levels.

The results obtained by our approach are shown in Table 2. Figure 5 presents the corresponding density plots for the different paths considering different levels of occupancy. Notice that the total time of the turnaround stage is reduced as the passengers' occupation level is decreased. In this case, the path related to disembarking, cleaning, and boarding the plane is the most frequent critical path, which is true regardless of the occupancy level: even with a 75% occupancy level, this path continues to be the critical one 95% of the time.

6 TESTING ALTERNATIVE DESIGNS

The results show that the disembarking-cleaning-boarding path was the most frequent critical one in all the considered scenarios. Therefore, any reduction in the duration of that path will have a positive impact on the turnaround time. The results also show that the less critical paths are those associated with catering, refueling, and maintenance processes. This indicates that the human teams dedicated to these paths are able to complete their assigned tasks before the end of the turnaround. Considering this fact, we changed the structure of the turnaround for the Boeing 737-800 by simply merging the fuel and maintenance tasks into a single path, so they are sequentially carried out by the same airline team instead of by two different teams.

The new design uses less paths than the original one: maintenance tasks are now performed right after refueling and by the same team. Both tasks take place outside the cabin, and thus they do not interfere

Table 1: Estimated average times for activities in the B737-800 aircraft.

		Occupancy levels:	**100%**	**90%**	**75%**
Type of activity	**Number**	**Activities**	**Time (min.)**		
Passenger Services	1	Deplane passengers	9	8	7
	2	Board passengers	14	12	10
	3	Catering (Service Galleys)	15	15	15
	4	Cleaning (Service Cabin)	11	11	11
Cargo handling	5	Unload cargo/baggage	6	6	6
	6	Load cargo/baggage	16	16	16
Airplane service	7	Fuel	9	9	9
	8	Maintenance	10	10	10

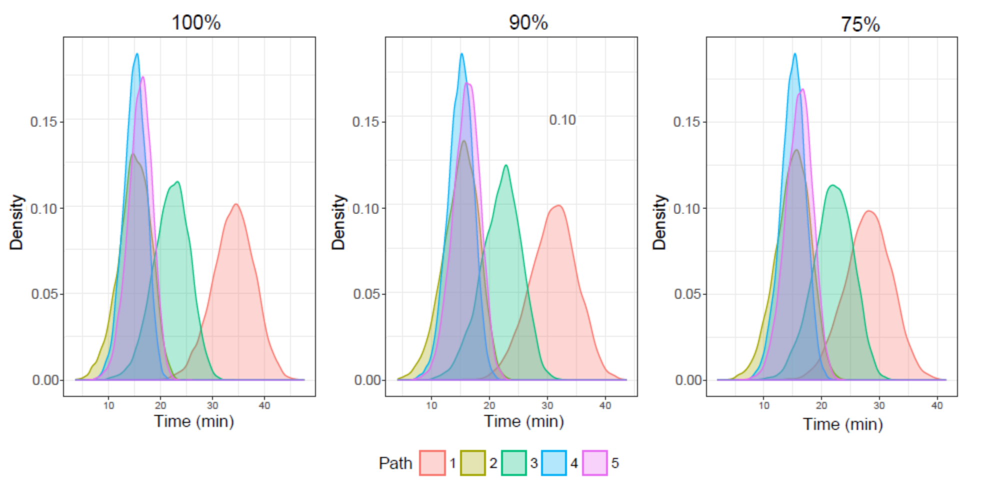

Figure 5: Density plot of activity paths for the Boeing 737-800 considering different occupancy levels.

with the ones being performed inside the cabin. Table 3 shows the new results provided by our approach for the different scenarios.

By comparing both designs, we can observe that turnaround average times are practically the same. Similarly, the most frequent critical path is still the previous one. However, the new merged path becomes critical in 20% of the cases. At the same time, with this simplified structure one less team is needed, and that team could be used to reinforce the cabin cleaning process, thus reducing the expected completion time of the critical path and, accordingly, the expected turnaround time. Even more interesting, this policy could modify the entire survival function (basically by shifting it to the left in Figure 3), which means that, at any target time, the probability of the turnaround stage being completed will be higher than it was before.

7 CONCLUSIONS

The aircraft turnaround process is a critical one for both airlines and airports. For airports, efficient turnaround process constitutes an opportunity to increase their overall capacity; for airlines, dealing with these processes in an optimal way can significantly reduce their associated cost.

This work proposes the combined use of simulation with survival analysis in order to analyze the different paths of activities that compose a typical turnaround process. As illustrated in the numerical experiments, our hybrid approach can be used not only to identify critical actions and paths in the process, but also to study potential benefits of different turnaround designs. Also, by introducing random times

Table 2: Estimated expected times for the turnaround stage - Original Design.

Occupancy 100% Average time: 34 min.			**Occupancy 90%** Average time: 31 min.			**Occupancy 75%** Average time: 28 min.		
Paths	**Longest**	**Shortest**	**Paths**	**Longest**	**Shortest**	**Paths**	**Longest**	**Shortest**
1	99.91%	0.00%	1	99.08%	0.00%	1	94.66%	0.00%
2	0.00%	41.70%	2	0.00%	41.82%	2	0.00%	41.65%
3	0.09%	0.06%	3	0.92%	0.08%	3	5.34%	0.05%
4	0.00%	40.12%	4	0.00%	40.03%	4	0.00%	40.38%
5	0.00%	18.12%	5	0.00%	18.07%	5	0.00%	17.92%

Table 3: Estimated expected times for the turnaround stage - Alternative Design.

Occupancy 100% Average time: 34 min.			**Occupancy 90%** Average time: 31 min.			**Occupancy 75%** Average time: 29 min.		
Paths	Longest	**Shortest**	**Paths**	**Longest**	**Shortest**	**Paths**	**Longest**	**Shortest**
1	98.50%	0.00%	1	92.85%	0.00%	1	76.79%	0.01%
2	0.00%	99.00%	2	0.00%	98.91%	2	0.00%	98.98%
3	0.02%	0.84%	3	0.28%	0.93%	3	1.35%	0.84%
4	1.48%	0.16%	4	6.87%	0.16%	4	21.86%	0.17%

instead of assuming a deterministic behavior, the analysis of the process is more realistic, and survival functions can be obtained for each of the proposed designs.

In future work, we plan to extend our simulation-based approach into a simheuristic algorithm by adding a metaheuristic optimization component. The idea here is to find the optimal design for the turnaround process, i.e., to find the feasible design that maximizes the probability that the turnaround process can be completed before a given deadline while respecting all the activity-precedence constraints.

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