A methodological framework to evaluate the impact of disruptions on airport turnaround operations: a case study

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A methodological framework to evaluate the impact of disruptions on airport turnaround operations: a case study

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Abstract

The efficiency and quality of airport airside operations are frequently compromised by various, unexpected disruptive events such as bad weather conditions, lack of handling staff and/or resources, strikes, aircraft diversions or technical failures, which may reduce airport airside operating capacity and affect the punctuality and regularity of the operations. In particular, disruptive events could lead to a substantial deviation of aircraft operations from the schedule, by causing the reduction of the system capacity and, thus, increasing congestion and flight delays, which worsen the overall performance of the air transport system. In this paper, the effects of unexpected events, particularly magnitude and duration, affecting airport airside operations are estimated within a general framework based on an element-by-element approach, adopted for the detailed representation and simulation of aircraft airside operations. The impacts generated by airport airside unexpected disruptions are modelled by using a discrete-event simulation model, dealing with both aircraft landing-and-takeoff (LTO) cycles and turnaround operations, developed and applied to the test case of a large regional airport.

1. Introduction

In recent years, the air traffic has been steadily growing in terms of both passengers and scheduled flights. In 2018, approximately 4.3 billion passengers used air transport scheduled flights, (+6.4 % on 2017), the number of departures reached approximately 38 million globally and 58 million tons of freight were carried by air transport (IATA, 2018). According to recent studies, in the next years the air traffic growth is expected to continue, with an annual rate of more than 4% for passengers and approximately 3% for cargo (ACI, 2017; ICAO, 2018).

Airports are crucial elements of the complex air transport system. They represent connection nodes where the continuous flow of arriving passengers is transformed into the set of discrete departures, i.e. scheduled flights. Airport operations rely on a complex architecture, in which different agents and facilities interact with each other by producing a set of deeply related activities (Humphreys and Francis, 2002; Ashford et al., 2013). Due to the high level of interconnection, if one of these elements fails to perform properly and efficiently, consequences spread quickly across the other connected activities. Furthermore, given the increasing number of aircraft movements and the size of recent airplanes, airports operate closer and closer to their capacity and frequently become bottlenecks and source of capacity constraints for the whole air transport network (Cohen and Paul, 2003). To be successful in the air transport competitive market, growing pressure is put on the different agents to conduct effective airport operations, as inefficiencies have important economic and social impacts (Clark et al., 2018; Cook et al., 2012).

In the last years, airport operations all over the world have been often jeopardized by unexpected and severe disruptive events - such as extreme bad weather, natural disasters of failures of airport components - which caused unexpected loss of airport capacity and serious delays. Such unpredictable events are called "disruptions", they can vary in size, cause and impact, can be interrelated and may occur simultaneously. In 2018, "*a record number of adverse weather events and industrial actions severely disrupted network operations*" (EUROCONTROL, 2018). Airport disruptions generally result in significant loss of airport capacity, sometimes causing the complete or partial closure of the airport, which implies diversion of current operations from the planned ones. Deteriorated airport operational performance generally results in flights delays, cancellations and diversions, which generate important economic losses and social impacts on the involved stakeholders: airport operators, airlines and passengers (Cook et al., 2009; Janic, 2009; Janic, 2015). As an example, according to some estimates provided by EUROCONTROL, one minute of flight delay costs European airlines 100€ on average, whereas each cancelled and diverted flight costs respectively 17,650€ and 7,400€ (EUROCONTROL, 2018). On the passengers' side, disruptions are major sources of dissatisfaction, anxiety and stress (Cook et al., 2009). These effects become more evident if the disruption happens during arrival or departure peak periods (Shavell, 2001). Because of the close interconnectedness between arriving and departing flights, even if only one airport is directly disrupted, negative effects may spread and undermine the regularity of operations at other aerodromes (Wu and Caves, 2002). Some disruptions might be so serious that knock-on effects could affect flight operations in an entire region or country (O'Regan, 2011). Besides, ground delays imply also additional fuel consumption and increased local and global atmospheric pollution, with a direct environmental impact through CO_2, CO, PM and NO_x emissions (Postorino et al., 2019).

Given the significance of the afore-mentioned impacts, growing interest on the topic has been expressed by the involved stakeholders and the research community, which recognized the need and significance of understanding how to reduce effects generated by disruptions. Some recent studies aim at evaluating the a-posteriori impacts caused by a specific disruptive event (Marzuoli et al., 2016) or focus on the estimation of the economic impacts due to the shutdown of an airport (Maertens et al., 2013; Serrano and Kazda, 2018). In Pejovic et al. (2009), also the impact in terms of CO_2 emissions is measured by using the RAMS Plus simulator. Several studies develop optimization strategies to relocate passengers and flights in light of an unexpected disturbance (Løve et al., 2002;

Kohl et al., 2007, Voltes-Dorta et al., 2017). However, the above studies focus mainly on the general evaluation of the effects of a disruption, without modelling the airport airside system and the specific and comprehensive operational consequences of a disruption. An attempt is provided in Janic (2009), where a deterministic queuing approach is developed for airport operations affected by a large-scale disruptive event such as persistent heavy snowfalls or hailstorms. However, deterministic models do not incorporate stochastic phenomena inherent in most airside operations, delay dynamics and their propagation (Yan et al., 2002; Rodriguez-Sanz et al., 2018).

The aim of this work is to propose a methodological framework to evaluate the effects generated by different types of potential disruptions affecting airport airside operations, by considering both landing and take-off (LTO) cycles, aircraft turnaround and the interrelations among them. The processes that make up these activities, and the related, involved resources, are represented according to an element-by-element approach (Postorino and Mantecchini, 2020) and simulated by using a discrete-event micro-simulation approach.

Macroscopic and microscopic simulation models have been already proposed in the literature to study airside operations and the interaction with existent infrastructure (Martinez et al., 2001). In many cases the analysis focus only on the runway-taxiway-apron system (Bubalo et al., 2011; Zuniga et al., 2011; Schinvald et al., 2016; Khammash et al., 2017) or on ground handling operations (Wu and Caves, 2004; Voulgarellis et al, 2005; Vidosavljevic and Tosic, 2010, Norin et al., 2012; Adeleye and Chung, 2006, Schultz, 2018), rarely considering both the processes as interrelated. However, only a few studies used a simulation approach to compute the consequences generated by potential airport disruptions (Damgacioglu et al; 2018).

The model proposed in this paper analyses the dynamics of each process as well as the whole system, in order to capture the consequences of disruptive events and potential knock-on effects on the different processes involved into the system. Moreover, constraints due to the limited infrastructure and amount of available resources of an airport are considered. Finally, some key performance indicators (KPIs) are defined to assess the effects of disruptions and possible areas of intervention by airport managers are identified. The methodology is applied to the case study of an Italian large regional airport, the Bologna "G. Marconi" Airport.

The remaining of the paper is organized in the following way. Section 2 describes the methodological framework proposed and the airside operations model. Section 3 describes the application of the methodology to a case study together with the obtained results. Finally, Section 4 discusses the results and summarizes the main findings, by highlighting possibilities for new researches.

2. Methodology

Airport disruption is a wide term which indicates unexpected events generally very different one from the other. Because of such diversity, the smooth functioning of airside operations may be hurt at different levels and moments of the process chain. The right understanding of which element is primary damaged, and how such damage causes performance inefficiencies of the related activities represents an important pre-requisite to identify proper actions and strategies to limit airside disruptions. Because of the complexity of the airside system, the methodological framework proposed in this work entails, as a first phase, the disaggregation of airside activities into a series of relevant sub-systems – *components* or *elements*. In the following sub-sections, the general element-by-element framework and its application to the airport airside are described.

2.1. Element-by-Element methodological framework

A complex system, like the airport airside, may be split into logical levels of components that have similar elements. Each element may be further split into subsystems up to the lowest hierarchical level referred to as "elementary" component. This is the base of the *element-by-element* (EbE) approach (Postorino and Mantecchini, 2020), which has been used here to identify which disrupted element provides the most relevant effect and how delays propagate among processes. In particular, airside activities have been divided into a first, highest, level of components with similar features, and each of them – or a part of them – have been additionally split into sub-activities, until the desired level of detail. Figure 1 illustrates the general framework of the EbE approach. The airside activity A is split into a first level of sub-activities $A_{1,\ldots,}$ A_n. Then, each sub-activity A_j is further split into a second level of elements A_{jr}. Components at the lowest levels – called "*elementary segments*" – correspond to the disaggregation level relevant for the aim of the analysis, and they depend on a vector of factors *F*.

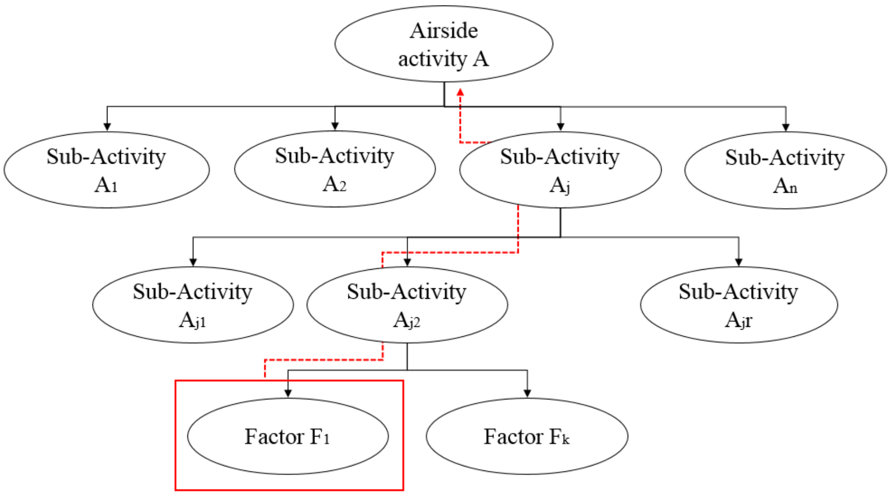


Figure 1. Element-by-element approach. Adapted from Postorino and Mantecchini (2020)

Airport processes usually occur sequentially or in parallel, leading to more or less complex representations, where the input factors and resources allocated to a certain activity generate new outputs that determine 1) performance levels of the specific and isolated activity, 2) output(s) that serve as input for other sequential and connected activities, propagating efficiencies or inefficiencies in the overall network that represents the system.

The EbE decomposition model developed in this work – and detailed in the following Section 2.2 - describes these processes for two main systems composing airside operations, namely the landing and take-off operations and turnaround procedures, and represents operations from the instant an incoming aircraft approaches the local airspace to the take-off of departing flights. All relevant activities A_j and variables are incorporated into the model, included the distances between the runway-taxiway-apron systems and the number of available stands. The elementary segments correspond to the ones that are directly affected by disruptions.

For the purposes of this work, the EbE approach, integrated with simulation, allows to identify the effects of the factors (F_i) on the specific activities (A) through the interconnected sub-activities (A_{ji}), testing - in particular - the consequences of any disruption involving temporary deficiencies, unavailability or inefficiencies of these same factors. In other words, the EbE decomposition provides the framework to simulate activities and allows identifying explicitly the most critical "element" in the whole process.

The disruptive event modifies the state of one or more factors (red rectangle in figure 1) and generates loss of performance in its related elementary segment and then in the linked activity. For example, if the disruption corresponds to the failure of a ground vehicle, the elementary segment is the activity for which such vehicle is needed, and the state of the factor reflects the unavailability of such vehicle. Given the high interconnectedness between activities, such reduced performance propagates among connected activities, by causing ripple effects that may influence activities up to the highest level (dotted red arrow in figure 1). The loss of performance for a given activity is expressed by some selected Key Performance Indicators (KPIs) – defined in Section 2.4 – that evaluate the amount of delay caused by the disturbance. Delays, for both departure and turnaround operations, are the primary and most evident effect on airside efficiency.

In this work, airside activities and disruptions are modelled by means of a discrete-event microsimulation model, implemented by using the software AnyLogic. Given the inherent complexity of the airport airside system, its dynamic and stochastic behavior, and the intrinsic variability of the delay propagation problem – which is even more evident in case of unexpected and uncontrollable disruptive events, when consequences with non-linear impacts are likely to arise (Damgacioglu et al., 2018) - simulation has been considered to be the most appropriate method for assessing the airport time-varying performances and analyzing the effects of unforeseen events.

Figure 2 summarizes the adopted methodology, which might be used to complement DSSs by identifying the best actions to minimize airside delays.

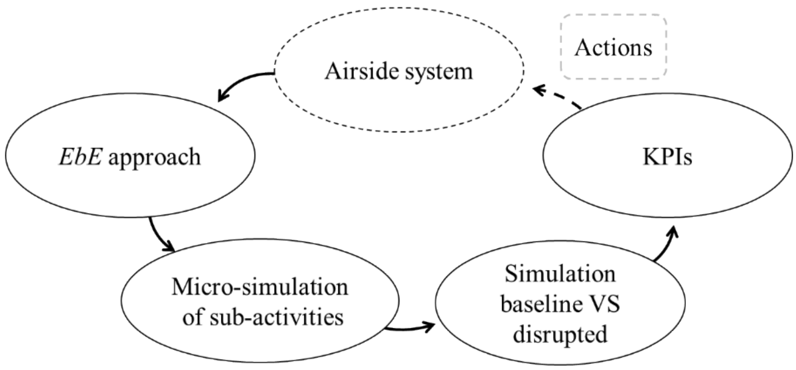


Figure 2. Methodological framework to estimate impacts of disruptions

2.2. Turnaround model within the EbE framework

By following the EbE approach, the high-level activities considered in this work are processes taking place during the LTO cycle, specifically: aircraft approaching, landing, taxi-in, turnaround, taxi-out and take-off. The attention here has been focused on turnaround operations, which allows to model the dependence of such activities from ground resources (operators and vehicles), and a more detailed level of decomposition has been considered for them. Thus, a second level of sub-activities describes aircraft handling at stands, including all relevant processes, such as passengers' disembarking and boarding, baggage loading and unloading, cleaning and catering, refuelling, waste water and potable water replenishment. Each of these processes has been further split into a third and last level of activities – elementary segments – which directly depends on the availability of ground resources, i.e. the vector of factors (Figure 3). It is worthwhile to note that many other types of airport disruptive events may be simulated within the proposed approach, by suitably setting the EbE structure.

Table 1 shows the decomposition of the turnaround activity (A_l) into its sub-activities (A_{lm}, A_{lmn},…) and the factors required to perform them.

Each one of the sub-activities can be performed only whether the resources necessary to undertake it are available (column “Factors” in table 1); if such resources cannot be used, the related processes are put on hold and have to wait until the necessary worker/equipment/infrastructure becomes available again. Resources are taken from the respective pool (blue rectangles in figure), whose capacity corresponds to the number of workers or equipment, or infrastructure characteristics of the airport under consideration. When an activity begins, the corresponding number of resources is occupied from the pool and, when the process is completed, they return available again (more details about the simulation of this process will be provided in the following section 2.3)

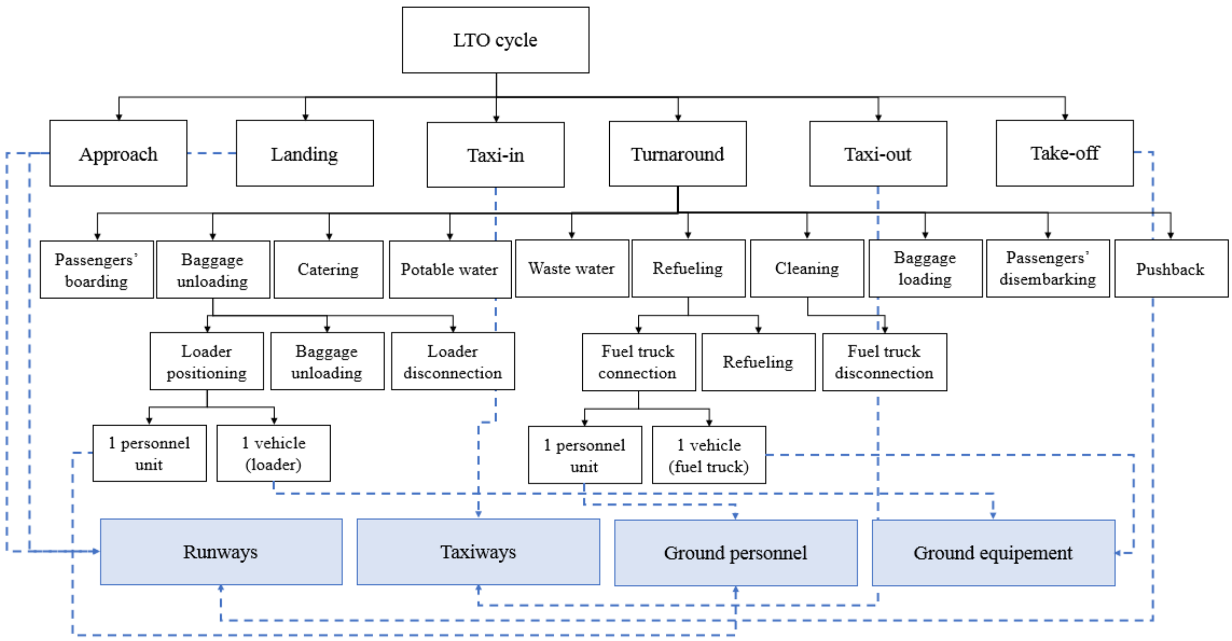


Figure 3. EbE framework for the LTO cycle main activity

Table 1. Turnaround activities

Sub-activity A_{lm}	**Sub-activity A_{lmn}**	**Factors**	
		N° personnel units	**Equipment**
Chocks on	-	1	-
Disembarking	Stairs positioning	2	Stairs
	Passengers disembarking	-	
Cleaning	Cleaning	2	-
Catering	Catering truck connection	2	Catering Trucks
	Departure catering loading		
	Arriving catering unloading		
	Catering truck disconnection		
Potable Water	Water truck connection	1	Water Truck
	Potable water replenishment		
	Water truck disconnection		
Waste water	Waste water truck connection	1	Waste water Truck
	Waste water		

	Waste water truck disconnection		
Baggage/Cargo Unloading	Loader positioning	3	Bulk/Container loader
	Arriving baggage/cargo unloading		
	Loader disconnection		
Refuelling	Fuel truck connection	1	Fuel Truck
	Refuelling		
	Fuel truck disconnection		
Baggage/Cargo Loading	Loader positioning	3	Bulk/Container loader
	Departing baggage/cargo loading		
	Loader disconnection		
Passengers boarding	Passengers boarding	-	Stairs
	Stairs removing	2	
Chocks off	-	1	-
Pushback	-	1	Tractor

At a given airport, each aircraft must undergo each – or a subset - of these activities, in a given sequence. Let *i(a,t)* be an arriving aircraft, characterized by the unique tail number *i*, operated by airline *a* and which is of the specific type *t*, i.e. narrow or wide body. Arrivals follow the order of the schedule and aircraft *i(a,t)* approaches the terminal manoeuvring area of the airport at time ta_i:

$$ta_i = STA_i - t_{approach} \qquad \text{(Eq. 1)}$$

where STA_i is the Scheduled Time of Arrival (*STA*) of aircraft *i(a,t)*. Each approaching aircraft is assigned to one of the runways of the airport; if such runway is not available, the aircraft waits by following a FIFO queue scheme; otherwise, $b_i(a,t)$ starts landing with a constant average deceleration d_i which depends on the length x_r of the runway:

$$d_i = \frac{1}{2}\frac{(v_1 - v_2)^2}{x_r} \qquad \text{(Eq. 2)}$$

where v_1 is the speed at the beginning of the braking phase, after the flare distance (i.e. the distance between the runway threshold and the actual touchdown point) and v_2 is the aircraft speed at the end of the braking phase (end of the landing). In the literature, average deceleration values varying in the range 1.9 – 2.3 m/s^2 can be found (Kim et al., 1996). After the landing, the aircraft goes to its assigned stand by using the shortest taxiways path. Stand assignment, which is not dynamic, depends on the aircraft size and airline, i.e. aircraft operated by low cost airlines are generally assigned to farthest stands.

Once arrived at the stand, ground handling operations are performed to prepare the aircraft for the successive departure. Turnaround sub-activities have to be performed in a precise chronological order: some of them have to be performed consecutively, others can be performed at the same time. After chocks positioning, passengers' stairs are placed - or a boarding bridge is connected to the aircraft. Then, passengers de-boarding can start as well as baggage and cargo unloading. Simultaneously, potable water is replenished; waste water servicing can begin only when potable water replenishment is finished (IATA, 2008). Cleaning and catering activities begin at the end of the passengers' disembarking process. Since refuelling generally is performed in the absence of passengers, it is assumed that such activity begins when the last passenger has left the aircraft. After the completion of the cleaning, catering and refuelling operations, passengers are boarded and, in the meantime, the cargo and baggage are loaded. Lastly, at the Scheduled Time of Departure STD_i of

aircraft $b_i(a,t)$, chocks are removed and pushback is performed with a duration $t_{pushback}$. Seasonal activities such as conditioning and de-icing are not included in this model.
During taxi-out, the aircraft arrives at the head of its assigned departing runway, where it waits for a time t_{vortex} to allow tail-vortices of the previous runway utilization to dissolve. Additional waiting times at the runway head may be due to expected landing of aircraft (approaching) within the next two minutes, because departing aircraft must give right-of way to landing ones. If the runway is available, the aircraft can take-off with an acceleration a_i equal to:

$$a_i = \frac{1v_3^2}{2x_r} \qquad \text{(Eq. 3)}$$

Where x_r is the length of the runway and v_3 is the rotation speed.

2.3. Simulation model

To evaluate the effects of disruptions during turnaround activities, and according to the selected KPIs (section 2.4), the whole LTO has to be simulated, although the disruption concerns only some elements of the turnaround activity.

As first step, the airport airside layout is represented by a graph. In particular, there are nodes, where operations effectively take place, and unidirectional links, which are used by entities to move from one node to another. Aprons are implemented as nodes with a limited capacity equal to the corresponding number of stands. Each link is assigned a length, corresponding to the distance between the two connected nodes. Taxiways are links in this network.

Each runway can handle a maximum number of movements (arrivals and departures) per hour; moreover, if there are restrictions regarding the use of the runway, they are explicitly taken into account - for example, runways that do not have the requirements to handle wide-body aircraft, or limitations related to environmental issues.

Each arriving aircraft (also defined as “Flight”) is generated according to a schedule, and processed in the simulation through a flowchart of processes. For each generated aircraft, the following information is stored in the Open Database Connectivity (ODBC): STA (Scheduled Time of Arrival), assigned runway to land, airline, ground handler, tail number of the aircraft, aircraft type (wide or narrow), STD (Scheduled Time of Departure), assigned apron and parking stand.

For each runway, a Boolean variable (“runway free”) indicates whether the runway is free or not. At the end of the approaching phase, each generated aircraft is allowed to land only if the runway is not occupied, otherwise it waits until the runway becomes free again. If the runway is free, the landing phase starts and the Boolean variable is updated to take into account the new state of the runway (occupied), which comes back again to the free status after the aircraft exits and a suitable time t_{vortex} has passed. Then, the aircraft arrives at the assigned stand, which becomes occupied and the apron available capacity decreases by one unit. If all the stands are occupied, the aircraft is sent to the nearest apron with one available stand. At the stand, each turnaround operation is implemented as separate process block. When entering each block, an aircraft seizes a given number of resource units, which belong to a set of “Resource Pools” with limited capacity, and after a given time releases them. If the pool is empty, the aircraft is put on hold. In disrupted conditions, the pool capacity decreases. One Resource Pool is defined for each of the following entities: handler operators, stairs, baggage loaders, water trucks, catering trucks, fuel tanks. When turnaround operations are completed, the aircraft move from its stand to the runway head by using as assigned path on the taxiway network. If the runway is occupied, the related Boolean variable is set accordingly and the aircraft is put on hold at the runway head. At the end of the take-off phase, i.e. when the departing aircraft clears the runway, the aircraft exits the system and data regarding the simulated departing time and potential departure delay are stored. A graphical overview of the model as implemented in AnyLogic is shown in Appendix B.

2.4. Disrupted turnaround condition and KPIs evaluation

Let *r* be the general resource, which can refer for example to ground vehicles or ground operators. When the airport is working under normal conditions, the number of resources that can be deployed is equal to the capacity of the resource pool, *R*. The disruptive event *d* occurring at the considered airport is here modelled as the reduction in the amount of available resources of the airport. The disruptive event causes a degradation of the service from the undisrupted value, by reducing the size of the resource pool.

When the disruption occurs, the number of available resources R_u - where the subscript *u* refers to the undisrupted situation - is reduced by a percentage P_d and the impaired amount of resources R_d becomes:

$$R_d = R_u * (1 - P_d/100) \quad \text{(Eq.4)}$$

If all resources in the pool are occupied, activities have to wait until the required resources are available again. This causes delays on the successive activities.

The impact caused by this type of disruption has been evaluated as the variation in performance expressed by a set of selected indicators taking into account delays at various levels, in particular:

1) Number of flights (%) departing late N_L
2) Total and average departure delay $DEL_{DEP,TOT}$ and $\overline{DEL}_{DEP}$
3) Variation in Average Turnaround Time

First of all, impacts are evaluated in terms of departure delay, a widely adopted indicator for airport airside efficiency (EUROCONTROL, 2018; Andersson Granberg and Munoz, 2013). It is assumed that a flight *i* is departing late if its actual time of departure (ATD_i) is more than 15 minutes higher than its STD_i. Then, the delay of the departing flight *i(a,t)* is:

$$\begin{cases} DEL_{DEP,i} = 0 \; if \; ATD_i - STD_i \leq 15' \\ DEL_{DEP,i} = ATD_i - STD_i \; [minutes] \; otherwise \end{cases} \quad \text{(Eq.5)}$$

and the total and average departure delay are given by, respectively:

$$DEL_{DEP,TOT} = \sum_{N_L} DEL_{DEP,i} \quad \text{(Eq.6)}$$

$$\overline{DEL}_{DEP} = \frac{DEL_{DEP,TOT}}{N_L} \quad \text{(Eq.7)}$$

where N_L is the total number of flights departing late N_L during the period of analysis T = 24h.

In addition, the variation in the average turnaround time in the aftermath of the disruption is evaluated. Turnaround time TAT_{iu} of aircraft *i(a,t),* under normal working conditions, is computed as the sum of the durations t_n of all turnaround activities A_{lmn}:

$$TAT_{iu} = \sum_{n} t_n \quad \text{(Eq.8)}$$

daily operations are carried out as specified in the schedule and turnaround time is the minimum time required to accommodate the aircraft and prepare it for the following flight. The average turnaround time is then given by:

$$\overline{TAT}_u = \frac{1}{N_{TOT}} \sum_{i=1}^{N_{tot}} TAT_{iu} \quad \text{(Eq.9)}$$

where N_{TOT} is the total number of processed flights during the period of analysis T.
Disturbances may cause an increase in turnaround time, which may or not result in departure delays. In fact, delays in turnaround operations may be balanced by buffer times that are often included in the schedule (Malandri et al., 2019, 2020; Wu, 2008). The variation in average turnaround time $\Delta \overline{TAT}_d$, given a disruption d, is evaluate as follows:

$$\Delta\overline{TAT}_d = \frac{\overline{TAT}_d - \overline{TAT}_u}{\overline{TAT}_u} \quad \text{(Eq.10)}$$

3. Case study: Bologna "G. Marconi" Airport

Bologna "Guglielmo Marconi" Airport (BLQ/LIPE) is an international airport in northern Italy. It is located approximately 6 km far from the centre of the city of Bologna. In 2018, it was ranked eight-busiest Italian airport, with more than 8.5 million passengers handled (+4% compared to previous year) of which 77% on international flights, and almost 70,000 movements (ENAC, 2019). In 2019, the airport has served more than one hundred destinations. Bologna airport has one runway (12/30 oriented, length 2,803 meters) with a capacity of 24 movements/hour. The airside layout, shown in figure 4, encompasses a ground network composed of one taxiway, ten Rapid Exit Taxiways (*RET*), three aprons used for scheduled airline services with a total of 29 aircraft parking stands, of which 3 for wide-body aircraft. Ground operations are operated by 2 different handling companies.

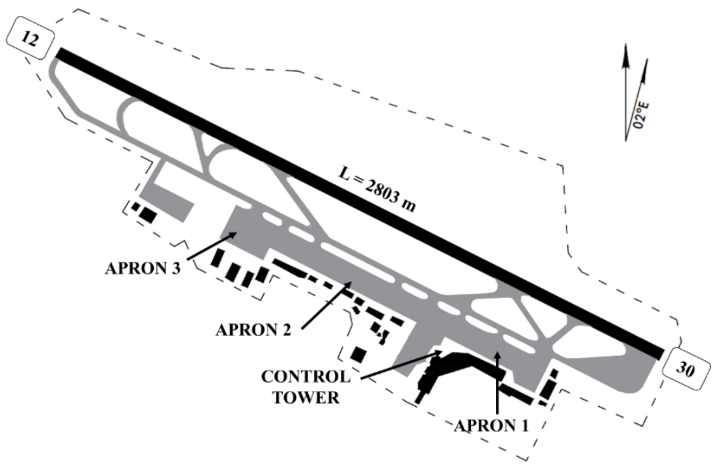


Figure 4. Bologna "G. Marconi" Airport airside layout

The simulation refers to an average peak summer day and for a period *T=24 h*. The flight schedule has been obtained by data available from Flightradar24 (www.flightradar24.com) and for each flight the following information are included: *STA*, flight number, airline, aircraft type (narrow or wide body) and tail number *i*. The latter is used to match the arriving aircraft with its next scheduled departure, in order to account for aircraft rotation. The schedule includes also the *STD* of the aircraft next departure. During the considered day, 107 flights are scheduled to arrive and 109 to depart, with a total of 216 movements during T (= 24 h). The scheduled traffic is composed of 96% narrow body aircraft, with a share of 35% of low-cost airline movements.

The assumption is made that runway 12 is used for landings as well as take-offs. Starting from Eq.1, aircraft are simulated at the beginning of the approaching phase, 2 minutes ($t_{approach}$) before their STA. At STA, if the runway is free, the aircraft starts landing with a speed v_1=75 m/s and occupies the runway. Under normal operating conditions, no arrival delay is considered, thus $ATA = STA$, where the ATA (Actual Time of Arrival) is the time the flight touches down. Between two subsequent runway utilizations, a time t_{vortex} must be considered, which is assumed to be equal to 60 seconds after narrow-body aircraft, 90 seconds after wide-body ones, in accordance with minimum separation standards (ICAO, 2007). On *RETs* and taxiways, aircraft move with a constant speed v_2 = 15 m/s and reach the assigned apron in approximately 3 minutes.

At stands, turnaround operations are performed by the handling companies operating at the airport. The following resources are assumed to be available during the simulated day: 20 personnel units, 6 fuel tanks, 10 bulk loaders, 6 water trucks, 16 stairs, 6 catering trucks. Such values are considered constant during the entire simulation period and personnel rotation is considered. The duration of each turnaround activity is assumed to be stochastic and described by a distribution function (see Appendix A); furthermore, some activities (potable and waste-water, refuelling, baggage and cargo loading/unloading) take double time for wide body aircraft. Time values are derived from aircraft manuals and literature (AIRBUS, 2017; Bevilacqua et al., 2015; Schmidt, 2017; Malandri et al., 2019), except for baggage unloading and loading operations that were calibrated for Bologna Airport (Briccoli et al., 2018).

Starting from the above assumptions, the simulation has been performed by using AnyLogic. To validate the simulation model, the *STD* is compared to aircraft's Actual Time of Departure (*ATD*) to check the consistency between the simulated times and real data and to verify that everything happens according to the schedule. Furthermore, to understand the extent to which the model depicts actual airport operations, the following checks are made, in order to ensure that: first, no ground activity takes place outside the simulation period; second, activities are carried out in the right order (e.g. refuelling takes place between de-boarding and boarding); third, each activity duration is consistent with literature and aircraft handling manuals. Since the developed model is stochastic, several runs have been performed to increase the accuracy of the results. In particular, the simulation has been repeated 20 times, to obtain an error lower than 5% for the average turnaround time and average departure delay. Figure 5 shows simulated (dashed line) vs scheduled (grey bars) aircraft departures during the simulation period *T*. As expected, in the absence of disruptions daily operations are carried out as planned, by confirming the average goodness of the model in reproducing real operations as well as the appropriateness of the amount of resources to accomplish on time the required activities. Peak periods can be observed between 10 AM and 1 PM, with 25 arrivals and 24 departures) and from 4 PM to 7 PM (20 arrivals and 24 departures. Turnaround operations have an average duration $\overline{TAT}$ = 44 minutes (minimum 29 and maximum 55 minutes), which is consistent with real operations and in line with previous literature (Fricke and Schultz, 2009; Mota et al., 2017).

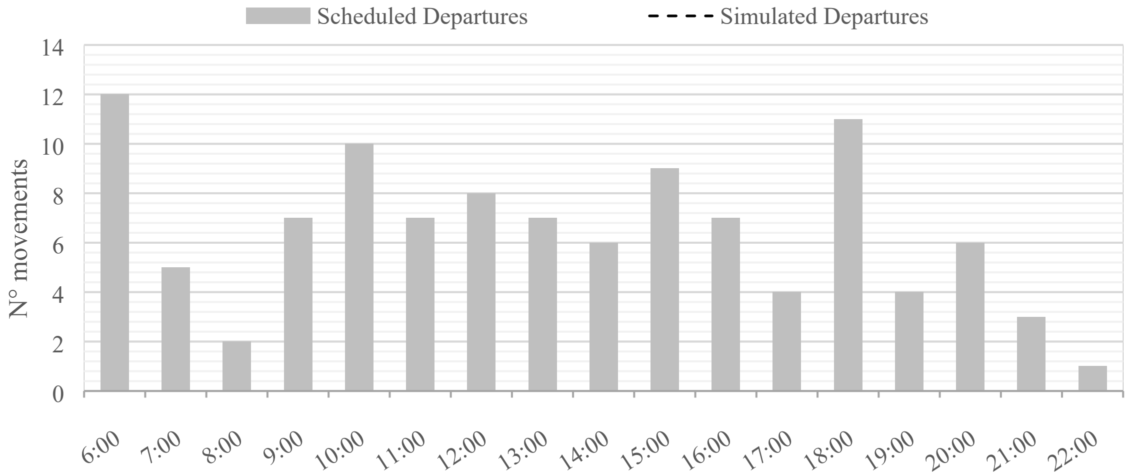


Figure 5. Arrivals and departures (simulated and scheduled) per hour during the simulation period.

Two different disruptive events are then simulated for the case study, both related to turnaround operations. In the first case, it is assumed that some ground vehicles are not available, for instance because of a technical failure or unscheduled maintenance. In the second case, the amount of personnel in service has been assumed lower than planned, for example for ground handlers' industrial actions. In both cases, various scenarios are examined by varying the amount of resources by different percentages P_d, according to Eq. 4, for the entire simulation period T. Table 2 and 3 show, respectively, the number of operators and ground vehicles for the different scenarios. As described in section 2, impacts are evaluated by computing the number of delayed flights, the average delay and the change in average turnaround time.

Table 2. Number of personnel units for the different scenarios

100 - P_d (%)	**100**	**90**	**80**	**70**	**60**	**50**
Personnel units	20	18	16	14	15	10

Table 3. Number of ground vehicles for the different scenarios

100 - P_d (%)	**100**	**90**	**80**	**70**	**60**
Stairs	16	15	12	11	10
Baggage loader	10	9	8	7	6
Fuel truck	6	6	5	4	3
Water truck	6	6	5	4	3
Catering truck	6	6	5	4	3

This simulation considers the number of available ground vehicles being lower than under normal operating conditions. Figure 6 shows the cumulative number of flight departures during the simulation period, in the baseline case and in the disrupted scenarios, which considers several values of P_d. Values in Figure 6 refer to average results. With a 10% and 20% decrease of ground vehicles, no delay is observed, and the number of departing flights are equal in baseline and disrupted scenarios.

With a 30% decrease, a slight offset is noticed from 10 AM until the end of the day. The higher deviation shows up during the peak period between 10 AM and 1 PM, because the high congestion contributes to lengthen the service time and thus increases the delay. However, such delay is absorbed within the simulation period, because in the evening the traffic to be handled is lower and inefficiencies accumulated previously can be recovered. The same comment can be made for the case with 60% resources available, where the curve shows a higher deviation during peak hours – especially between 6 and 7 PM - which is recovered faster during the evening. As shown in Table 4, the simulated disruptions involving the number of available vehicles has small impacts (about 1 minute) on both average turnaround time and average delay, with only a slight increase in the number of aircraft departing late. With a 60% of available ground vehicles, there is a change of just 77 seconds (2.88%) compared to the baseline case, which is linked to the good daily schedule of operations.

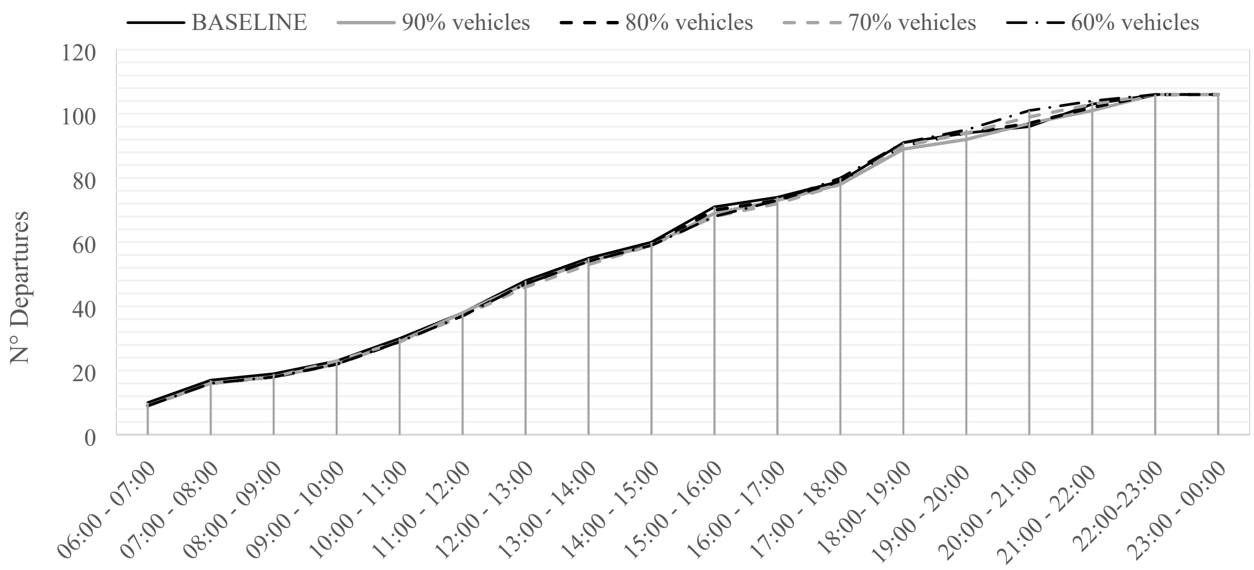


Figure 6. Cumulative number of departures during the simulation period with different numbers of ground vehicles

Table 4. KPIs as a function of the different amount of available resources (vehicles)

SCENARIO	**baseline**	**90% vehicles**	**80% vehicles**	**70% vehicles**	**60% vehicles**
Average TAT	00:44:33	00:44:33	00:45:14	00:45:34	00:45:50
St. Dev. TAT	00:35:48	00:35:45	00:35:31	00:35:46	00:35:44
Average Delay	00:04:42	00:04:29	00:04:58	00:05:16	00:05:37
St. Dev. Delay	00:08:28	00:08:09	00:08:37	00:09:12	00:09:30
% Dep on-time	14.15%	14.15%	16.04%	16.98%	18.87%

When the disruption involves ground operator personnel, the situation becomes more critical, as personnel units perform actions for longer time windows than vehicles. Figure 7 shows the cumulative number of aircraft departures when the number of operators is lower than the baseline situation, by decreasing available personnel units at constant steps equal to 10%. As before, values are averaged over the different experiments performed for each simulation. With a 10% decrease some delay occurs (35% of flights delayed, as shown in Table 5). With further decreases (20% and 30%), delays become significant and propagate during the entire day. In all these cases, however, delays are absorbed during the evening period and all scheduled flights depart before midnight. These situations could still be managed, although around 50% aircraft depart late (see Table 5) when there are 70% available operators. Particularly, 54 flights are delayed by more than 1,5 h. Below a certain threshold (60%), the situation worsen dramatically (average turnaround of more than 4 hours) and many flights depart after midnight (approximately 20%) or could be cancelled. Table 5 reports the average turnaround times computed for each scenario. Results show that serious operational inefficiencies arise when the number of available operators decreases. With a reduction of 10%, turnaround time increases by 6 minutes (13%), while further reductions generate significantly longer turnaround times. In this case, each activity put on hold due to missing workforce blocks all the following activities for the same aircraft and delay becomes more significant.

By considering both 80% personnel and 80% vehicles, such balanced reduction of personnel and vehicles has almost the same effect than a reduction of the same size of workforce only, thus suggesting that major impacts are caused by the ground personnel shortage.

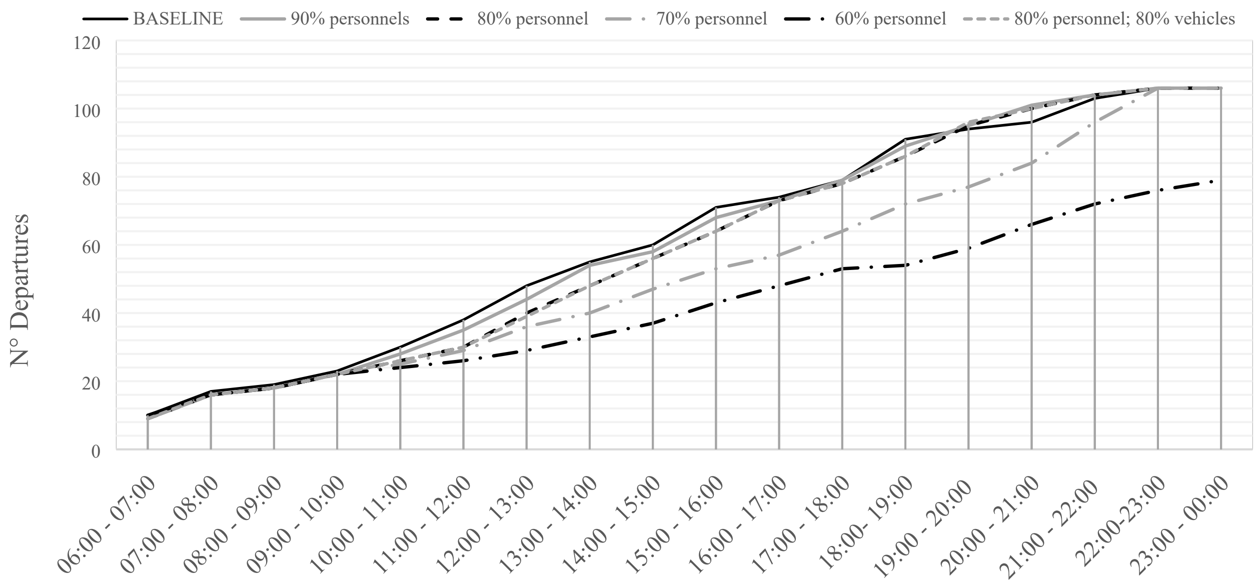


Figure 7. Cumulative number of departures during the simulation period with different number of available personnel units

Table 5.

KPIs as a function of the different amount of available resources (personnel units)

SCENARIO	baseline	90% personnel	80% personnel	70% personnel	60% personnel	80% vehicles 80% personnel
Average TAT	00:44:33	00:50:33	01:04:40	02:07:07	04:04:16	01:05:22
St. Dev. TAT	00:35:48	00:35:50	00:37:42	00:45:27	01:39:33	00:37:34

Average Delay	00:04:42	00:10:06	00:19:05	01:11:17	02:38:41	00:19:41
St. Dev. Delay	00:08:28	00:12:14	00:21:16	00:47:58	01:57:24	00:21:20
% DEP on-time	14.15%	34.91%	48.11%	77.36%	67.92%	52.83%

4. Discussion and conclusions

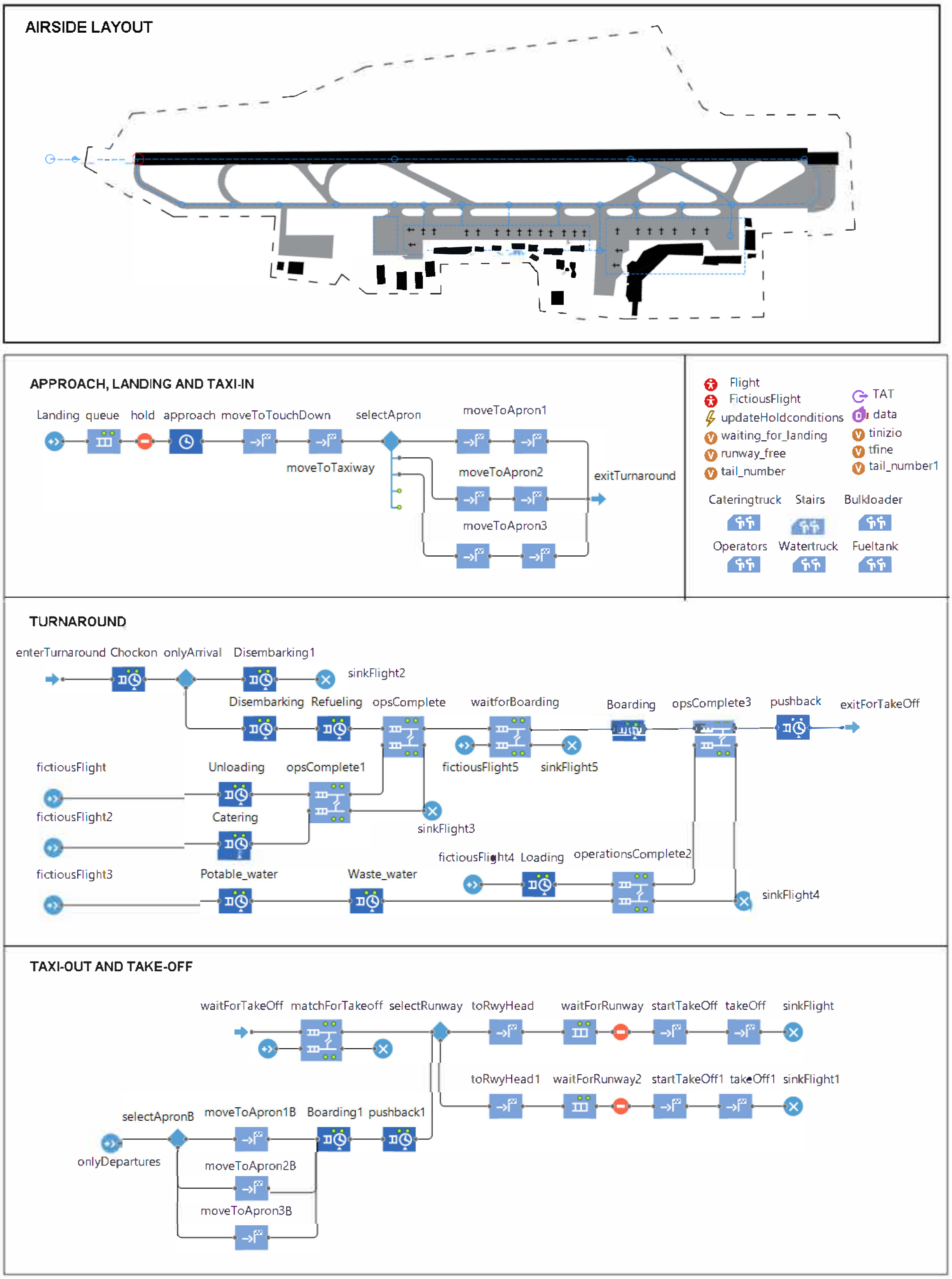
Results obtained from the application described in section 3 allow gaining some important insights. As a first comment, the effects of disturbances on airside operations largely depend on the type of disruption and the affected factors, which have been identified within the proposed EbE approach. In fact, as the application to the test case has showed, different factors affected by disruption produce different impacts on the same elementary segment. While the unavailability of a certain number of ground vehicles affects slightly the normal operability, so that the performance is almost the same between baseline and disrupted scenario, disruptions involving ground personnel are much more relevant and produce significant impacts. In the tested case, also for disruption affecting 50% of vehicles, delays on turnaround activities are not excessive, and only a few flights depart late. On the contrary, if just a slight disruption involves ground personnel the performance is highly compromised and delays propagate during the entire day. In fact, simulations have showed that if only 20% of personnel units are not operational, almost 50% scheduled flights are forced to depart late. When the number of available ground operators is about 60%, delays become unbearable and flights may be delayed until uncongested periods (i.e. in the evening) or even cancelled. In this situation, the average turnaround is more than three times longer than in the baseline scenario, a significant number of flights experience considerable delays, and both airline and handler suffer from financial losses. In addition, in case of a high number of cancellations, the apron physical capacity would lack and aircraft would be forced to stay on the ground until airlines' re-scheduling of the new departing flight. The identification of factors for elementary segments within the EbE approach has allowed to identify which one is more relevant when concurrent disruption may occur. In the tested case, the simultaneous occurrence of both disruptive events – vehicles and ground personnel – has showed that ground personnel are a key parameter for containing delays. It is worthwhile to note that this result depends on the airport features of the tested case, such as layout, number of runways and configuration of the ground network, which have been considered as a fixed input in the simulation model. However, the important result is that the adopted segmentation of activities within the EbE framework has allowed to identify which factor is more relevant in case of disrupted conditions, by keeping unvaried some other airport features. In addition to previous comments, the simulation approach has detailed each activity coherently with the EbE structure that has been defined for the LTO cycle and the turnaround activity in particular. By setting a suitable framework within the AnyLogic tool, the stochastic nature of the airport activities and sub-activities have been simulated by proper functions.

To summarize, the methodology developed in this work is able to represent the complex airside processes at successive levels of detail, which at the end focus on the elementary segments and relevant factors where effective actions may be adopted. Together with the EbE segmentation approach, the dynamic and stochastic nature of airside (elementary) activities has been simulated in order to estimate how delays propagate from one activity to the other. This methodological framework may complement a Decision Support Systems (DSS) helping airport and handling operators to develop strategic planning of the service, to achieve enlarged system robustness and to minimize loss of efficiency. Further developments are expected in this field. While in this study impacts have been estimated as delays, which are considered to be the primary, direct effect of disruptions, however, impacts of disruptions are manifold and further research might include the estimation of pollutant and noise externalities and the impacts perceived by the different stakeholders due to service disruptions and traffic departing in late evening. In addition, the simulation model and the EbE structure could include also seasonal activities (i.e., de-icing and air conditioning) and constraints on workforce shifts and rotas. Although this work focuses on the disruptions that can occur during the aircraft turnaround process, the same methodological approach can be adopted to evaluate the effects of any disruptive event that can affect other phases of the LTO cycle and, more in general, any other airport air-side process

Appendix A - Distribution functions for turnaround activity

Sub-activity A*lm*	Sub-activity A*lmn*	t_n
Chocks on	-	30 secs
Disembarking	Stairs positioning	TRIANGULAR (1.8, 2, 2.3 min)
	Passengers disembarking	20 pax/min
Cleaning	Cleaning	TRIANGULAR (13, 16.5, 19.5 min)
Catering	Catering truck connection	TRIANGULAR (0.85, 1.05, 1.2 min)
	Departure catering loading	TRIANGULAR (7,8, 9 min)
	Arriving catering unloading	TRIANGULAR (3, 4, 5 min)
	Catering truck disconnection	TRIANGULAR (0.95, 1.15, 1.3 min)
Potable Water	Water truck connection	TRIANGULAR (0.65, 0.8, 0.95 min)
	Potable water replenishment	TRIANGULAR (4, 5, 6 min)
	Water truck disconnection	TRIANGULAR (0.45, 0.6, 0.85 min)
Waste-water	Waste-water truck connection	TRIANGULAR (0.65, 0.8, 0.95 min)
	Waste-water	TRIANGULAR (4, 5, 6 min)
	Waste-water truck disconnection	TRIANGULAR (0.45, 0.6, 0.85 min)
Baggage/Cargo Unloading	Loader positioning	TRIANGULAR (40, 60, 80 sec)
	Arriving baggage/cargo unloading	TRIANGULAR (5, 7, 9 min)
	Loader disconnection	TRIANGULAR (40, 60, 80 sec)
Refuelling	Fuel truck connection	TRIANGULAR (0.7, 0.9, 1.2 min)
	Refuelling	TRIANGULAR (7, 8, 9 min)
	Fuel truck disconnection	TRIANGULAR (1.0, 1.2, 1.4 min)
Baggage/Cargo Loading	Loader positioning	TRIANGULAR (40, 60, 80 sec)
	Departing baggage/cargo loading	TRIANGULAR (5, 7, 11 min)
	Loader disconnection	TRIANGULAR (40, 60, 80 sec)
Passengers boarding	Passengers boarding	12 pax/min
	Stairs removing	TRIANGULAR (1.0, 1.3, 1.6 min)
Chocks off	-	30 secs
Pushback		TRIANGULAR (3.0, 4.0, 5.0 min)

Appendix B – Graphical overview of the model implemented in AnyLogic



AIRSIDE LAYOUT
APPROACH, LANDING AND TAXI-IN
Landing queue hold approach moveToTouchDown selectApron moveToApron1
moveToTaxiway moveToApron2 exitTurnaround
moveToApron3
Flight
FictiousFlight
updateHoldconditions
waiting_for_landing
runway_free
tail_number
TAT
data
tinizio
tfine
tail_number1
Cateringtruck Stairs Bulkloader
Operators Watertruck Fueltank
TURNAROUND
enterTurnaround Chockon onlyArrival Disembarking1
sinkFlight2
Disembarking Refueling opsComplete waitforBoarding Boarding opsComplete3 pushback exitForTakeOff
fictiousFlight Unloading opsComplete1 fictiousFlight5 sinkFlight5
fictiousFlight2 Catering
sinkFlight3
fictiousFlight3 Potable_water Waste_water fictiousFlight4 Loading operationsComplete2
sinkFlight4
TAXI-OUT AND TAKE-OFF
waitForTakeOff matchForTakeoff selectRunway toRwyHead waitForRunway startTakeOff takeOff sinkFlight
toRwyHead1 waitForRunway2 startTakeOff1 takeOff1 sinkFlight1
selectApronB moveToApron1B Boarding1 pushback1
onlyDepartures
moveToApron2B
moveToApron3B

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HIGHLIGHTS

- A framework is proposed to determine impacts of airport airside disruptions
- Airport airside operations are modelled by using an element-by-element approach
- A discrete- event simulation model is built of both LTO and turnaround operations
- The model allows to capture knock-on effects on successive operations
- The methodology is illustrated through the case study of a large Italian airport