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HOW TO COPE WITH AIR TRANSPORT DISRUPTIONS: AIRPORT AIRSIDE RESILIENCE AND VULNERABILITY

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ABSTRACT

The efficiency of airport airside operations is often compromised by unplanned disruptive events of different kinds, such as bad weather, strikes or technical failures, which negatively influence the punctuality and regularity of operations, causing serious delays and unexpected congestion. The disruptive events affecting airport nodes make operations substantially deviate from the schedule, causing either the complete closure of an aerodrome as a whole (and consequently downing the capacity to zero) or the reduction of the system capacity (thus, increasing the flight delays). They may provoke important impacts and economic losses on passengers, airlines and airport operators, and consequences may propagate in the whole air network throughout different airports. In order to identify strategies to cope with such events and minimize the impacts on both passengers and service providers, it is crucial to understand how disruptive events affect airports' performance. The research field related with the risk of severe air transport network disruptions and their impact on society is generally related to the concepts of "vulnerability" and "resilience". In particular, vulnerability refers to the impacts of unexpected disruptive events that could undermine the whole system, while resilience describes the ability of a system to cope with such circumstances and recover from them. In recent years, the research concerning resilience has grown considerably and is nowadays a major challenge in system's design. However, while resilience and vulnerability have been largely studied in a plethora of fields, little research has focused on airport airside operations.

The main objective of this project is to provide a framework that allows to evaluate performance losses and consequences due to unexpected disruptions affecting airport airside operations, supporting the development of a methodology for estimating vulnerability and resilience indicators for airport airside operations. Such approach allows to estimate the consequences of a wide range of disruptions and could be used to predict the impacts cause by those events.

The methodology proposed comprises three phases. In the first phase, airside operations are modelled in both the baseline and disrupted scenarios. The model includes all main airside processes and takes into consideration the uncertainties and dynamics of the system. In the second phase, the model is implemented by using a generic simulation software, AnyLogic, and validated by applying it to four known disruption cases. The effects caused by a disruption are evaluated by means of specific indicators, which are generally expressed in terms of delays and loss of capacity, and by computing resilience and vulnerability indexes. Specifically, vulnerability is evaluated in terms of equivalent cancelled flights, weighted by taking into

consideration the costs related to flight delays, cancellations and diversions. Besides, resilience is determined as a function of the loss of capacity during the entire period of disruption. The simulation model is then applied to a large number of real disruptions, obtaining a database with 135 cases in which different disruptive events hurt the performance of several European airports. In the third phase, the database obtained has been used to build a Bayesian Network in which uncertain variables refer to (i) airport characteristics, (ii) disruption features and (iii) parameters indicating the impact caused by the disruption on the system. The Bayesian Network expresses the conditional dependence among these uncertain variables and allows to predict the impacts of disruptions on an airside system, determining the elements which influence the system resilience the most.

The contribution of this work can be summarized into three main points. First, the simulation model developed allows to evaluate knock-on effects – in terms of delays - of disruptive events on as a function of the available resources. Second, synthetic resilience and vulnerability are introduced which considers both the loss of airside capacity and the recovery time, as well as the costs related to flight delays; such metrics allows to compare the effects of different types of disruptions on different airports. Third, a Bayesian Network approach to resilience is proposed, which allows to determine the probabilistic dependence among variables of interest and to predict the consequences of airside disruptions. The framework proposed could be used to determine the elements most critical in the system and develop strategies and actions to mitigate the consequences of such events.

CONTENTS

LIST OF ACRONYMS

- AB: Agent Based
- ATA: Actual Time of Arrival
- ATC: Air Traffic Control
- ATD: Actual Time of Departure
- ATFM: Air Traffic Flow Management
- ATM: Air Transport Management
- BN: Bayesian Network
- CPT: Conditional Probability Table
- DAG: Direct Acyclic Graph
- DE: Discrete Event
- EATN: European Air Transport Network
- FIFO: First In First Out
- IATA: International Air Transport Association
- ICAO: International Civil Aviation Organization
- ILS: Instrument Landing System
- LCC: Low Cost Carrier
- LTO: Landing and Take-Off
- ROC: Receiving Operating Characteristics
- RWY: Runway
- SD: System Dynamics
- STA: Scheduled Time of Arrival
- STD: Scheduled Time of Departure
- VOR: Very High Frequency Omnidirectional Range

NOTATION LIST

a	Airline
A	Airport
ac_k	Aircraft acceleration
ATR	Average Throughput Rate
CAP	Hourly capacity
CL	Capacity Loss
$COST_c$	Cost of a cancelled flight
$COST_d$	Cost of a diverted flight
$cost_r$	Cost of one minute of delay
$COST_r$	Cost of a delayed flight
d	Aircraft deceleration
D	Disruption
DEL	Flight departure delay
DEL_{DEP}	Arrival delay
DEL_{DEP}	Departure delay
ET	Effective Throughput
ETR	Effective Throughput Rate
i	Turnaround operations
j	Ground handler operator
J	Number of available operators
k_A	Arriving aircraft
m	Ground handler
M	Number of ground handlers
MAX_{queue}	Maximum waiting aircraft at runway head
N_{ARR}	Number of arriving flights
$N_{ARR,DEL}$	Number of flights arriving late
N_C	Number of cancelled flights
N_D	Number of diverted flights
N_{DEP}	Number of departing flights
N_L	Number of flights departing late
N_{TOT}	Total number of aircraft movements (arrivals and departures)
o_i	Turnaround sub-operations

$P_{m,d}$	Percentage reduction of available ground operators
R	Number of runways
r	Runway
RED	Percentage reduction in airport capacity
re_i	Turnaround resources (vehicles)
RES	Resilience indicator
s	Aircraft parking stand
T	Period of analysis
t_{1k}	Chocks-on time
t_{2k}	Chocks-off time
ta	Time of arrival at the terminal manoeuvring area
$t_{approach}$	Time for the approaching phase
TAT	Turnaround time
$t_{cancelled}$	Maximum delay before cancellation
t_d	Disruption duration
$t_{diverted}$	Maximum waiting time for landing before diversion
TI	Total impacted flights
TL	Turnaround Loss
t_{oi}	Duration of turnaround sub-operation o_i
$t_{pushback}$	Pushback duration
t_r	Recovery time
t_t	Time of performance deviation
t_{vortex}	Minimum time between two subsequent runway utilizations
V	Vulnerability indicator
v_l	Aircraft speed at the beginning of the landing phase
v_t	Aircraft speed at the end of the take-off phase
v_{taxiin}	Aircraft speed on taxiways
w	Aircraft type (wide or narrow-body)
x_r	Length of the runway

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1. INTRODUCTION

1.1. How to cope with disruptions?

Air transport is a critical factor to the well-functioning of the world economy. 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 (ICAO, 2018). The air traffic has been steadily growing in recent years, showing a growing demand and reliance on air transport in terms of both passengers and scheduled flights.

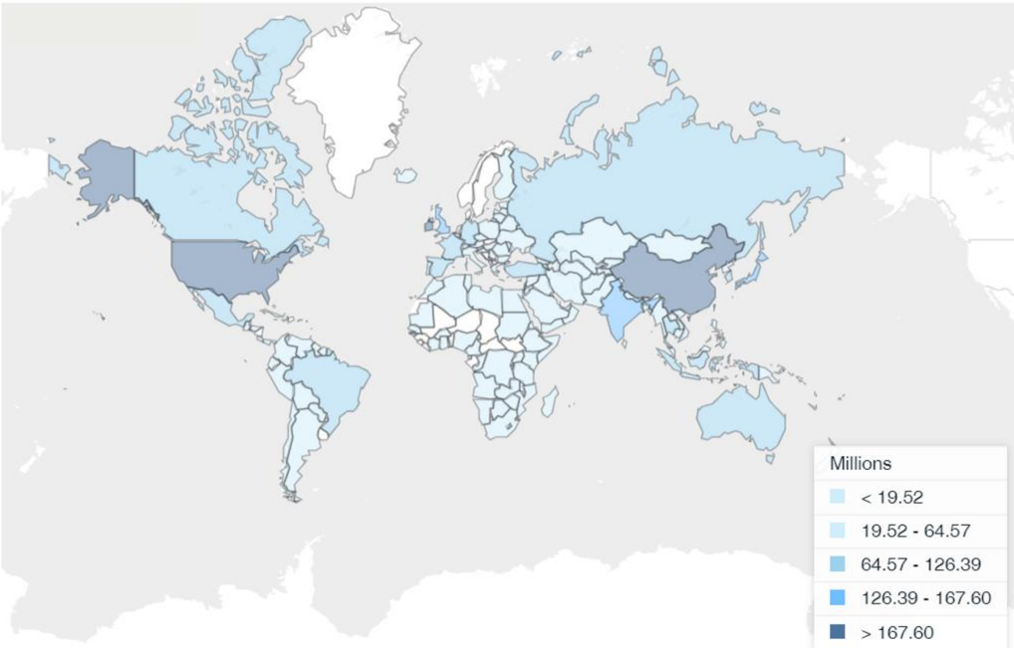


Figure 1.1. Passengers carried by air transport in 2018. Source: https://data.worldbank.org

The air transport system is composed of a high number of technological, humans and organizational elements which interact with each other and create a complex large-scale organism. The mobility of passengers is just the final result and it is clearly of high importance from a social point of view. The failure or inefficiency of one of those elements is likely to cause dramatic consequences and high economic costs.

Many recent events have shown that the air transport system is particular susceptible to airport disruptions. One well-known example is the eruption of Iceland's Eyjafjallajokull volcano on April 13th, 2010, which produced a high plume of gases and ashes which spread over most Europe. This event caused several air spaces closures lasting for more than a week – between 14 and 24 April – resulting in the cancellation of about two thirds of European flights and about 180 transatlantic flights in a single day (Reichardt et al., 2018, 2019, ICAO, 2010). Both flight cancellation and delays propagated much broader, reaching Canada and Japan. The IATA (International Air Transport Association) estimated that the total cost of impacts for the global airline industry had been of about 1.7 $US billion. Some others remarkable examples are Hurricane Katrina (2005), the Haiti earthquake (2010) and the Pakistan floods (2010), which exposed the vulnerability of air transport and its weaknesses (O'Regan, 2011).

The research field related with the risk of severe air transport network disruptions and their impact on society is generally related to the concepts of "vulnerability" and "resilience". In particular, vulnerability refers to the impacts of unexpected disruptive events that could undermine the whole system, while resilience describes the ability of a system to cope with such circumstances and recover from them. The resilience of air traffic networks is therefore of great importance, in order to minimise the impacts on the stakeholders involved and the economic losses due to disruptive events. In recent years, the research concerning resilience has grown considerably and is nowadays a major challenge in system's design.

In the dynamic and large-scale system which is the air transport, airports represent the connection nodes between aircraft movements through the air network and passengers' transport modal changes (de Neufville & Odoni, 2003). They rely on a complex architecture, in which various agents and facilities interact with each other (Ashford et al., 2013), creating a complex combination of interconnected components. Airports are usually a source of capacity constraints for the entire network; furthermore, given the increasing number of aircraft movements and the size of recent aircraft, airports are increasingly becoming bottlenecks for air traffic flow. Therefore, airports represent a fundamental element in air transport regarding safety, passenger experience and operations' efficiency (Ashford et al., 2011).

However, the efficiency of airport operations is often compromised by unplanned disruptive events of different kinds, such as bad weather, strikes or technical failures, which negatively influence the punctuality and regularity of operations, causing serious delays and unexpected congestion. These unplanned disruptive events may have different nature and impact, can be interrelated and occur simultaneously.

The disruptive events affecting airport nodes make operations substantially deviate from the schedule, causing either the complete closure of an aerodrome as a whole (and consequently downing the capacity to zero) or the reduction of the system capacity (thus, increasing the flight delays). Moreover, service disruptions at a particular airport – incident, failures and delays - may cause degradation in the whole air network by propagating throughout the different airports (Wu and Caves, 2004).

For example, the Asiana crash at San Francisco airport in 2013 led to cancelations, delays and diversions at the airport and impacted the rest of the airspace with knock-on effects. On July 6th, the instrument landing system vertical guidance on runway 28L was, as scheduled, out of service. In addition, in the morning, an aircraft crashed just short of runway 28L's threshold. The crash resulted in a five-hour total closure of the runways at the airport, with the cancellation and diversion of all flights. Even after the airport reopened, its capacity was reduced by more than a half. Summing the results over four days, more than 660 arriving and 580 departing flights at San Francisco airport had either been cancelled or diverted (Marzuoli et al., 2016).

Airport disruptions result in important delays, cancellations and rerouting of the affected aircraft, provoking important economic losses for airline and airport operators. Furthermore, delays have also a considerable impact also on airport passenger experience, customer satisfaction and system reliability (Cook et al., 2009). Disruptions are a key source of passengers' dissatisfaction and their discontent - missed meetings, lost personal time, anxiety and stress - may eventually undermine customers' loyalty and lead to up to boycott the airlines, with inevitable loss of business. Moreover, there may be additional costs imposed on airports, airlines, and air passengers – which are potentially the most affected stakeholders - due to mitigating actions such as delaying, cancelling and rerouting.

It is thus crucial to understand how disruptive events affect airports' performance, and to identify strategies to cope with such events, minimizing the impacts on both passengers and service providers.

1.2. Aim and description of the project

The scope of this thesis is to develop a framework to evaluate the impacts generated by unexpected airport disruptions. In particular, airport systems consist of two areas: landside and airside, with security control as boundary between the two (see figure 1.2). In this work, the analysis is focused on airside operations, indicated in red in Figure 1.2.

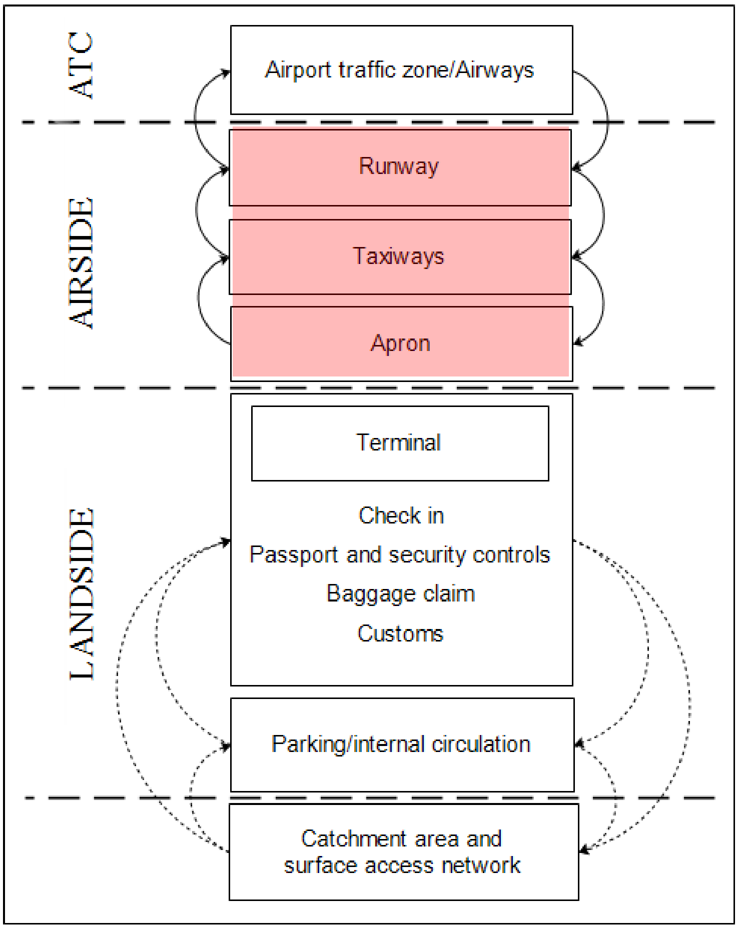


Figure 1.2. Airport system

Then, the aim of this project is to develop a methodology to determine airport airside vulnerability and resilience; such framework could be easily used to evaluate and predict the impacts generated by disruptive events affecting airside operations. The main aim is achieved by accomplishing three sub-objectives:

1) determining the consequences of disruptive events affecting airport airside systems to evaluate the impacts on the main stakeholders involved - such as airports, airlines and passengers;

2) defining synthetic metrics capable of estimating the resilience and vulnerability of airports' airside operations affected by an unexpected disruptive event.
3) understanding the causal relationships between impacts, airport characteristics and disruption type, within a probabilistic approach.

Towards this aim, the methodology proposed entails three main phases.

In the first phase, the airside (apron - runway - taxiway) system is modelled. Most elements in such system are subject to uncertainties, making airside operations a stochastic phenomenon (Rodríguez-Sanz et al., 2018). The stochastic and time-varying nature of the operations create a set of dynamics which influence the way the system evolves and how airlines and airport service providers and operators manage their operations. This is even more emphasized in case of unexpected and uncontrollable disruptive events. The model developed in this thesis is capable of analysing the dynamics of each process and of the whole system, in order to better capture the consequences of disruptive events and potential knock-on effects. Moreover, constraints due to the limited amount of available resources will be considered. The proposed framework models an airport ground network in a comprehensive way by considering both its technical aspects (i.e. scheduled flights, runway configuration) and inherent system uncertainties. The model developed consists of two main systems, namely the landing and take-offs processes and turnaround operations, and represents operations from the moment an aircraft approaches the local airspace to the take-off for departing flights. All main factors and processes are included in the analysis in order to make the model as realistic as possible.

Then, a disruption is modelled which hurts airside operational performance. However, the disruptions affecting airside operations may be very different from each other and influence the performance in different ways. Thus, as a preliminary step to this phase, an historical analysis is performed of airport disruptions in recent years, and the different disruptions are then clustered depending on the airside process which is primarily affected. The clustering allows to model in the same way disruptions belonging to the same cluster. Once the disruptions have been identified, a disrupted model is built for each cluster.

In the second phase, both the undisrupted and disrupted model are implemented by using a generic simulation software, AnyLogic. In fact, given the complex and stochastic nature of airside operations, and uncertainties related to the effects of disruptive events, simulation was reckoned to be the most proper tool in order to analyse and measure airport's disrupted and undisrupted performance. The simulation model generates outputs of time-dependent measures of performance at different levels. Models are validated by comparing simulations' output with real data and the variation between the new state and the baseline state is measured as the change of selected performance indicators. Such gradient reflects the impact of disturbances and allows to identify the most critical processes. Specifically, impacts are evaluated in terms of flight delays and cancellations. Moreover, some indicators are defined to evaluate the vulnerability and resilience of the system.

However, the simulation model provides information regarding the overall impact, without specifying how much each single element – process or variable – influence the resulting performance loss. In other words, the variation of certain elements may cause higher ripple effects on the successive operations, provoking more serious consequences on the functioning of the system. Then, in the third and last phase a Bayesian Network (BN) is developed. BNs are excellent tools for determining the probability of the impacts that a disruption of a certain type might cause on a generic airport, thus relating variables of interest related to both the disruption type and airport characteristics.

Consequently, the main contribution of this work to the existing literature is manifold:

- First, the methodological approach proposed is based on a simulation a simulation model that allows to evaluate knock-on delays as a function of the amount of the available resources.
- Second, this thesis addressed the topic of resilience in airside operations and, despite the importance of the topic, it has been poorly addressed in the literature.
- Third, resilience and vulnerability metrics are proposed for airside operations. While a plethora of qualitative definitions have been proposed in the last years, only a few studies propose metric to quantitatively evaluate it.
- Moreover, a Bayesian Network approach is proposed to deal with the topic of resilience; this is a quite novel approach and only a few studies adopt it.

The methodology is intended to provide a methodological framework which can be used to forecast and assess the consequences of disruptive events affecting airport systems and can support the identification of strategies that could mitigate the impacts of disruption.

1.3. Thesis outline

The remaining of the thesis is structured as follows.

In Chapter 2, the concepts of resilience and vulnerability are introduced and described. In Chapter 3, the literature related to resilience in the field of transportation is reviewed. In particular, a comprehensive review is provided of resilience and vulnerability studies in the context of air transport operations. The review is structured at three different level: the global air transport network, the airline level and the node (airport) level. Chapter 4 provides insights regarding airport disruptions. Specifically, the disruptions happened in the last four years (from 2015 to 2018) have been analysed and clustered. In Chapter 5 the methodological approach adopted in this work is detailed and the airside operations models are described, both in the reference and in the disrupted scenarios. The methodology described has been implemented by using a generic simulation software. Chapter 6 provides the reasons of choosing a simulation-based approach, then described the simulation software used (AnyLogic) and then how the model has been implemented. Then, the implemented model has been applied to four different disruption cases and results are presented in Chapter 7. Then, the simulation model has been used to simulate disruptions of the last five years, in order to build a database in which airport properties, airport characteristics and impacts are. The database is used to build a Bayesian Network (Chapter 7) which allows to predict and assess the dependencies among airport features and disruption's characteristics.

2. BACKGROUND

2.1. Resilience interpretations

Initially, the term resilience has been introduced in the field of mechanics and material testing by Hoffman (Hoffman, 1948). From that moment, the term *resilience* has attracted rapidly growing attention in different research domains and is nowadays an extremely popular term. To date, the topic is widely studied, and several books and papers have been published on resilience.

The word resilience originates from the Latin verb "*resilio*", which means to "spring back". The Oxford dictionary (Stevenson, 2011) defined the term resilient as follows:

"Resilient (adjective)

- *(of a substance or object) able to recoil or spring back into shape after bending, stretching or being compressed;*
- *(of a person or animal) able to withstand or recover quickly from difficult conditions."*

Therefore, the general use of this word indicates the ability of a system or entity to return to normal conditions after the occurrence of an event that disrupts its state. This can be the case, for example, of individuals who overcome a great trouble, or cities and communities recovering after a natural disaster (Henry & Emmanuel Ramirez-Marquez, 2012).

In the scientific literature, the term has been interpreted in different ways depending on the research field. Among the diverse meaning and interpretations of the concept of resilience, three main forms of resilience can been identified which summarize previous literature (Filippone et al., 2016).

The first form is referred to as "*engineering resilience*". As specified in Hoffman (1948), this interpretation focuses on the stability near an equilibrium steady state, on the resistance to disturbance and on the speed of return to the equilibrium (Hoffman, 1948), following the removal of the disturbance factor. It can be stated that this form concentrates on efficiency, constancy and predictability and resilience is intended as the ability of a system or substance – or the time required - to return to an equilibrium state (Pimm, 1991). It should be noted that Hoffman describes this inherent ability of a substance by using the term "resiliency"; however, the word "resilience" indicates a wider property which considers also the size and shape of the object (Gluchshenko & Foerster, 2013).

The second form is denominated "*ecological resilience*". Holling, in his most famous work (Holling, 1973), introduced the concept resilience for ecological systems. Here, resilience is defined as "*the persistence of systems and their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables*" (Holling, 1973). After a few years, the same author re-examined the definition in order to place more importance on the preserved aspects instead of the disturbance. Resilience was thus redefined as "*the ability of a system to maintain its structure and patterns of behaviour in the face of disturbance*" (Holling, 1985). A third definition was provided in 1996 by Holling, which sharpens previous ones: "*resilience is the buffer capacity or the ability of a system to absorb perturbations, or the magnitude of disturbance that can be absorbed before a system changes its structure by changing the variables and processes that control behaviour*" (Holling, 1996b). Then resilience is intended here as the capacity of a system to absorb disturbance and reorganize, in order to retain still the same function and identity (Walker et al., 2004). This second interpretation of resilience focuses therefore on disturbances that can push a system into another equilibrium state and concentrates on persistence, change and unpredictability (Filippone et al., 2016).

As specified in (Holling, 1996a), the first two forms of resilience address contrasting aspects: whereas engineering resilience focuses on maintaining efficiency of a function, ecological resilience focuses on maintenance of a function. Then, on one hand, ecological resilience would then reflect whether the system returns to the same state or function after some external shocks; on the other hand, engineering resilience refers to the rapidity of its recovery to the full level of function.

A third form of resilience has been introduced by Hollnagel in 2006 (Hollnagel et al., 2006), which is referred to as "*resilience engineering*". This interpretation is especially directed to socio-technical systems and includes a set of techniques to ensure resilience, i.e. "*the intrinsic ability of a system to adjust its functioning prior to, during, or following changes and disturbances, so that it can sustain required operations under both expected and unexpected conditions*" (Hollnagel, 2011), and also "*a paradigm for safety management that focuses on how to help people cope with complexity under pressure to achieve success*" (Hollnagel, 2016). It concentrates on the ability of a socio-technical system to deal with the unexpected in order to comply with reliability and safety objectives. Thus, resilience engineering aims at designing systems that are able to continue functioning even when facing with adverse events and it is considered as a discipline in the domain of safety and performance analysis. Differently from the previous interpretations, this concept of resilience focuses more on proactive processes rather than reactive ones (Hollnagel et al., 2006).

Afterwards, the term has generated a lot of interest in different scientific communities and is nowadays applied to a plethora of fields, including psychology (Dent & Cameron, 2003), ecology (Gunderson, 2000; Walker et al., 2004), biology (Orwin & Wardle, 2004), human organizations (Weick & Sutcliffe, 2013), economics (Rose, 2007), systems safety (Hollnagel et al., 2006), computer science (Nakayama et al., 2007) and many others.

However, with the increased popularity of the topic, also confusion has grown about the meaning of the term. In fact, even if the common understanding of the concept is to recoil after being affected by a disruption, several definitions have been proposed, each one focusing on certain aspects more than others, and the label "*resilience*" has been used in multiple different ways. Then, it is not unambiguously clear how the concept of resilience is defined, and in recent years the need has arisen for an agreed and clear definition.

In the following, the focus will be directed to the third form of resilience, the so-called "*resilience engineering*". In fact, air transportation, as well as transportation systems in general, is a socio-technical system, and it belongs to the domain of resilience engineering. In the following, thus, we will focus on the third interpretation of resilience.

2.2. Resilience: qualitative definitions

Due to its role in reducing the risks associated with the unavoidable systems' disruption and economic importance, in recent years the interest in resilience engineering grew exponentially (Patriarca et al., 2018).

Are contained within the resilience engineering domain all of that systems in which an interaction exists between technology and people, including, electric power networks and infrastructure systems such as, among others, the water distribution system and the transportation systems.

In the last decade, following Hollnagel's work (Hollnagel et al., 2006), several interpretations have been suggested of resilience engineering, and currently many definitions exist of resilience, creating confusion and preventing a common understanding of the term. Different efforts have been made to define and quantify it, with many more qualitative formulations that quantitative definitions being proposed. In the following, an overview will be provided of the definitions present in literature from a qualitative point of view and, in the successive Section 2.3, the principal quantitative metrics proposed. From now on, the term “*resilience*” will refer only to research within the framework of “*resilience engineering*”.

Among all the definitions proposed, four main streams can be identified, which address different aspects of the concept (Haimes, 2009):

1. Resilience is the ability of a system to absorb external and internal stresses;
2. Resilience refers to the inherent ability and adaptive responses of systems that enable them to avoid potential losses;
3. Resilience is a system capability to create foresight, to recognize, to anticipate and to defend against the changing shape of risk before adverse consequences occur (Deary et al., 2013);
4. Resilience is the result of a system (1) preventing adverse consequences, (2) minimizing adverse consequences, and (3) recovering quickly from adverse consequences (Westrum, 2018).

In the first stream, the definitions given interpret resilience as an inherent ability of a system to passively reduce harmful effects of an external disturbance. (Pregenzer, 2011) defines resilience as “*the measure of a system’s ability to absorb continuous and unpredictable change and still maintain its vital function*”. Another example can be found in the definition given by the American Society of Mechanical Engineers (ASME, 2009), according to whom resilience as the ability of a system to withstand external and internal disruptions without discontinuity in the correct functioning of the system or, if the function is disconnected, to rapidly recover to the full performance. Also the U.S. Department of Homeland Security (DHS) defined resilience as the “*capability of an asset, system, or network to maintain its function during or to recover from a terroristic attack or other incident*” (DHS, 2006).

In the second group, an additional aspect is introduced which refers to the ability of a system to adaptively respond to stresses in order to reduce degradation. These definitions include bot passive mechanisms to absorb stress and active processes to adapt to the stress condition. (Rose & Liao, 2005) define resilience as “*the inherent and adaptive response that enables firms and regions to avoid maximum potential losses*”. In (Cutter et al., 2009), resilience is intended as the ability of a system “*to respond and recover from disasters and includes those inherent conditions that allow the system to absorb impacts and cope with an event, as well as post-*

event, adaptive processes that facilitate the ability of the social system to re-organize, change and learn in response to threat".

In the third view, resilience is interpreted tightly connected to the concept of risk. This intimate relation is illustrated in a recent exchange between two researchers. In 2009, Haimes states that "*resilience is the ability of a system to withstand a major disruption within acceptable degradation parameters and to recover within acceptable time and composite costs and risks*" (Haimes, 2009). Improving a system's resilience constitutes an advantage in managing risks; more explicitly, given the probabilistic nature of threats, given the occurrence of a class of threat scenarios, the outputs (consequences) are best represented with probability distribution functions, as well as the recovery time and composite costs. Resilience depends on the system's state development over time. In a parallel paper, (Aven, 2011) challenge the definition given by Haimes and states that the uncertainty dimension is not reflected as adequately as it should be, especially regarding the likelihood of the system's state. In fact, after considering all the variables at a given point in time, a low probability of a system being endangered due to the event corresponds to high resilience of the system and vice versa.

In the fourth and last category, three main aspects of resilience are highlighted: the ability to anticipate adverse events, of absorbing the impacts and to recover quickly to normal functionality. In these definitions, resilience derives not only from responding to adverse situations, but also from anticipating and monitoring, thus preventing negative outcomes. Moreover, in these group, more emphasis is put on the recovery aspect. The National Infrastructure Advisory Board (NIAC) defines infrastructure resilience as the "*ability to reduce the magnitude and/or duration of disruptive events. The effectiveness of a resilient infrastructure or enterprise depends upon its ability to anticipate, absorb, adapt to, and/or rapidly recover from a potentially disruptive event*" (NIAC, 2009). Similarly, (Cook et al., 2015) suggest the following key properties for resilience: "*resilience is an ability to respond to disruption through recovery; the response may be measured in terms of its magnitude, and its temporal and spatial extent. The magnitude may be expressed with respect to system performance targets*". (Vugrin et al., 2010) defines system resilience as follows: "*given the occurrence of a particular disruptive event (or set of events), the resilience of a system to that event (or events) is the ability to reduce "efficiently" both the magnitude and duration of the deviation from targeted "system performance levels*". The two last definitions emphasize that a fundamental property of resilience is the "recovery effort", which is the amount of resources expended during the recovery process.

Then, resilience engineering provides a socio-technical framework to cope with disruptions and threats through preparedness, response, recovery and adaptation (Worton, 2012). This is expressed in (Hollnagel, 2016) in terms of four cornerstones of resilience, i.e. four abilities that represents resilient systems (illustrated in figure 2.1):

1. Knowing what to do (*responding*): respond to threats and disturbances either by adjusting normal functioning or by implementing a prepared set of responses;
2. Knowing what to look for (*monitoring*): monitor what may became a threat in the short time, both in the external environment and in the system itself, that is, its own performance. Knowing what to expect (*anticipating*): anticipate future threats, such as potential changes, disruptions, pressures, and their consequences.
3. Knowing what has happened (*learning*): learn lessons from past experience, both from successes and failures.

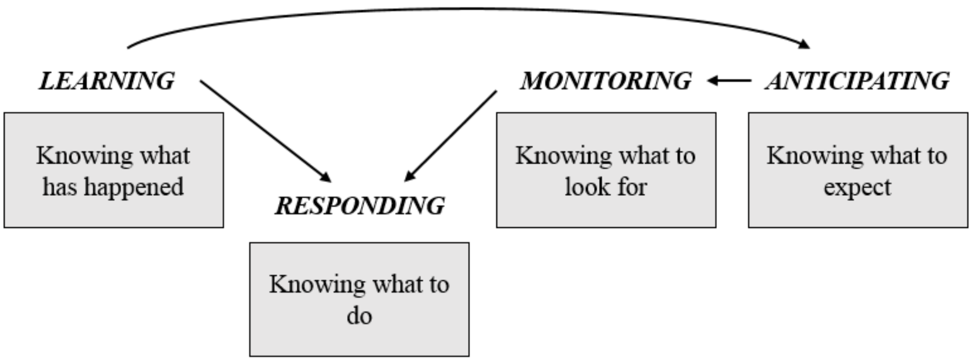


Figure 2.1. The four cornerstones of resilience. Adapted from (Hollnagel, 2016)

Moreover, (Bruneau et al., 2003) outlines that a resilient system should have four main attributes, that were denoted as "*4rs*": *robustness* is the ability to withstand a given level of stress; *redundancy* is the extent to which system's failed element can be substituted without reducing the performance of the system; *resourcefulness* expresses the ability to mobilize resources when conditions exist that threaten to disrupt some element, system or other unit of analysis; *rapidity* is the ability to respond in a timely manner in order to contain losses and avoid future disruption.

Recently, several reviews have been conducted which tries to summarize previous literature. An overview of the resilience concept and its various dimensions, mainly in the context of socio-economic systems, can be found in (Francis & Bekera, 2014). They conducted a survey of resilience definitions in various domains, including economic resilience, critical infrastructure resilience, resilience as a safety management paradigm; organizational resilience and others. Similar reviews can be found in (Hassler & Kohler, 2014), (Hosseini et al., 2016), (Woods, 2015).

In particular, among all definitions, Woods (Woods, 2015) identified four core concepts of resilience, recurring in all the different perspectives and disciplines. He classifies the diverse conceptual perspectives into four groups, denominated *Resilience 1 to 4*. The first concept (*Resilience 1*) is identified with the term "*rebound*" and focuses on how a system recoils from a traumatic event (or *surprise*) and returns to previous (normal) activities. Specifically, the attention is not focused on the period of rebound, but on what capabilities and resources were present before the disruptive event (Colvin & Taylor, 2012; Deary et al., 2013). In Finkel's analysis (Finkel & Tlamim, 2011), evidence is provided which confirms that the ability to recover is not affected by what happens after a surprise, but depends on which capacities, present before the surprise, can be mobilized or deployed to deal with the shock. The second interpretation (*Resilience 2*) deals with the increased ability to absorb perturbations and tends semantically to the concept of "*robustness*". An increased robustness helps expanding the set of disturbances the system can effectively deal with, without collapsing (Alderson & Doyle, 2010; Doyle & Csete, 2011). However, this definition implies that, when the system is challenged by an event outside the current set, the system will experience a sudden failure, meaning that the system is brittle at its boundaries, which leads to the third concept of resilience. Moreover, recent studies pointed out that expanding the system's ability to handle with some events often cause the system to be vulnerable to other kinds of events (Woods, 2017). The notions of "*resilience*" and "*robustness*" has been often confused and considered as overlapping, causing even more noise on the topic. The relation between resilience and robustness will be addressed more in detail in Section. *Resilience 3* has been labelled with the term *graceful extensibility*. This interpretation understands resilience the ability to extend adaptive capacity when handling surprise, thus seeing it as the opposite of *brittleness*. Brittleness describes the rapidity of system's performance degradation when it nears its boundaries, thus defining how a system behave near and beyond its boundaries. Differently from previous interpretations, this one focuses on how systems stretch to face surprises (Woods & Wreathall, 2008; Woods, 2017). Systems with high *graceful extensibility* are able to anticipate bottlenecks and failures. The fourth core concept refers to the ability to manage adaptive capacities of complex systems, and it is referred to as *Resilience 4 – sustained adaptability*. This interpretation asks the question: "what is the property of a layered network that produces the ability to adapt to future surprises as conditions?" and explores methodologies to assess the sustained adaptability of a system as well as the techniques that would allow to design a system producing sustained adaptability.

Even if the definitions illustrated above diverge on some aspects, several commonalities can be observed among all of them. The main aspects are summarized as follows:

- Resilience is considered as a desirable and positive aspects that systems should have;
- There is an initial disruptive event, which can be internal or external to the system, that causes a degradation in the system's performance;
- All definitions include aspects of withstanding a disruption; many of them focus on the capability of a system to "absorb" or to "adapt" to disruptive events;
- Many definitions consider the rate of recovery as a factor contributing to resilience: considering the same context, a system is considered more resilient if it recovers faster. In many works, the recovery aspect is retained to be the critical aspect of resilience;
- Some definitions emphasize that returning to a pre-disaster performance level is essential for resilient systems, instead in other interpretations it is necessary that the system returns to the steady state performance level (Gunderson, 2000);
- Some definitions put stress on the ability to be prepare and anticipate disruptive events.

It is therefore clear that, with the increased interest in the role of system resilience, also confusion about how to qualitatively assess resilience has grown. However, what emerges is that resilience is a conceptual framework composed of multiple dimensions, and literature seems to converge in the direction of a common definition of those dimensions. Specifically, a resilient system should have three main properties to respond to perceived or real shocks, in order to maintain its original functionality. These three properties, denoted in (Vugrin et al., 2010) with the term "*resilience capacities*", are absorptive capacity, adaptive capacity and restorative capacities (see figure 2.2):

- Absorptive capacity is an endogenous property of the system and is defined as the degree to which a system can automatically absorb the impacts of system's disruptions, minimizing consequences with little effort.
- Adaptive capacity is the ability of a system to endogenously re-organize itself to return to pre-disruption performance levels.

- Restorative capacity is the ability of a system to restore its original functioning, or to restore to a completely new state. Differently from adaptive capacity, which usually includes actions that changes radically the structure of the system, the restorative one involves repairs to return at the original structure.
- Last, but not less importantly, the system should be able to anticipate potential threats in order to pre-dispose pre-disruption preparatory actions.

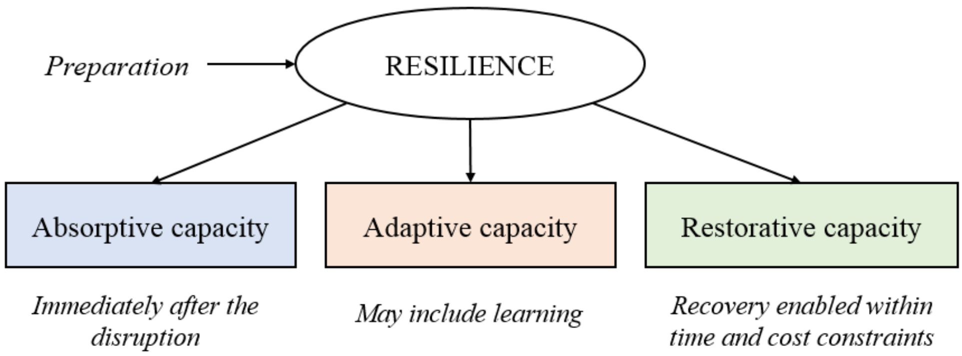


Figure 2.2. Resilience capacities

2.3. Resilience: quantitative metrics

Along with the need of an agreed qualitative definition of resilience, it has been acknowledged that quantitative metrics are required to support resilience engineering. In fact, quantitative metrics provide direct measurement that can be used to assess disaster impact, mitigate them and undertake adaptive actions. Several attempts have been made in the past, but less than qualitative formulations. This section describes the main quantitative resilience assessment approaches developed in previous research.

From the qualitative framework provided in the previous section, it emerges that a quantitative measure of resilience should consider the following factors:

- there is an initial disruptive event which affect the correct functioning of the system;
- resilience should measure how a system behave during and a after a disruption, that is how a disruption affects system performance and causes degradation in system's productivity, with respect to a specific performance level;
- the recovery depends on the amount of resources and on the structure of the system.

In literature, general measures of resilience provide quantitative metrics which determine the performance of the system, independently of the system's characteristics. In these measures, resilience is assessed by comparing the pre-disruption performance with the performance during and after the disruption, without concentrating specifically on system's structure.

This approach has been adopted with similar underlying logic in different system contexts. Generally, resilience is assessed by considering as starting point the curve in Figure 2.3 (Wan et al., 2017). The curve shows a system's hypothetical performance as a function of time, in normal and disrupted conditions. The horizontal one displays the time, while the vertical axis shows system's performance, which is usually measured with operational metrics.

Overall, the system's performance when facing disruptions can be divided into three main phases, namely pre-disruption, disruption and post-disruption phases; moreover, the disruption stage is composed of a response and a recovery period:

1) *Pre-disruption phase*, for $t < t_1$: in this stage, the system is in its normal state and it operates as planned. This period is dominated by reliability, which is defined as "*the probability of a device performing its purpose adequately for the period of time intended under the operation conditions encountered*" (Billinton & Allan, 1983). Reliability allows the system to provide the required service function without failing (Baroud et al., 2014; Zhou et al., 2019). Here, preparation should be included to enhance the resourcefulness and redundancy of a system.

2) *Response phase*, for $t_1 < t < t_2$: a disruptive event happens at time t_1 which causes a degradation in system's performance. The degradation continues until time t_2, when the system's performance reaches the lowest level. At this time, the negative effects are fully released. If the performance doesn't drop below a minimum required level threshold, the system remains in the robustness domain. Otherwise, if the minimum acceptable performance level is crossed, the system is in the resilience domain and both robustness and redundancy influence the initial reduction in system's performance.

3) *Recovery phase*, for $t_2 < t < t_3$: at t_2, the negative effects of the disruption are completely released, and the system's recovery begins. Immediately after the beginning of the disruption, the system responds in order to mitigate negative consequences and recovery strategies are adopted to regain system's functionality as fast as possible. Different recovery actions might be taken, each one having different costs and thus influencing

differently the system. Here, rapidity emphasizes the speed of returning to the original state. The shape of the performance curve depends on the amount of resources available.

4) <u>*Post-disruption phase*</u>, for $t > t_3$: after time t_2, the system settles to a restored performance level. This new equilibrium could be either the one operated before the disruption event or a completely new state, i.e. an improved or partially recovered state. Experience from the previous disruption should contribute to the preparation of potential future disruptive events.

The different phases of a time-dependent resilient system affected by a disruption are illustrated in Figure 2.3, which tries to provide a comprehensive view of the topic and to include all principal concepts.

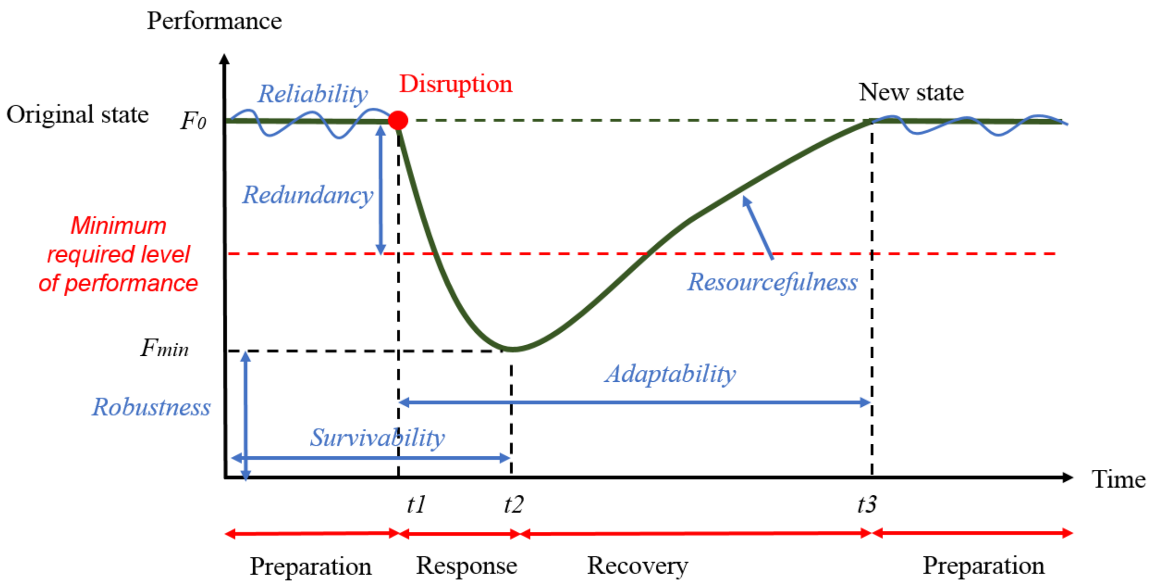


Figure 2.3. Performance of a resilient system affected by a disruption. Adapted from (Wan et al., 2018)

Each of these phases refer to a different resilience capacity, as shown in figure 2.4. The pre-disruption phase refers to the capacity the anticipate potential threats (anticipation capacity), while the response and recovery phases refers, respectively, to the absorptive and restorative capacities. The adaptive capacity could manifest during the entire disruption phase. Last, the post-disruption stage becomes the anticipation phase for a possible future new disruptive event, where the anticipation capacity is enhanced by learning from the previous disruption.

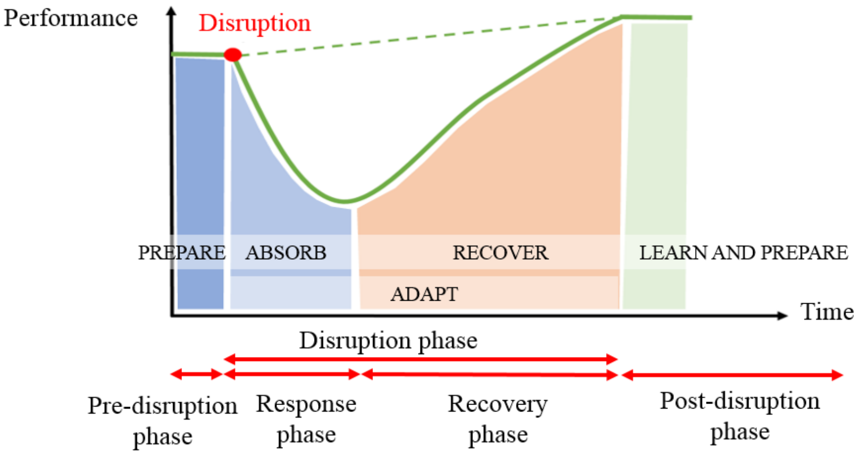


Figure 2.4. Performance of a system affected by a disruption and resilience capacities

Several attempts have been made in the last years to try to quantify resilience. Reviews can be found, for example, in (Hosseini et al., 2016), (Faturechi & Miller-Hooks, 2015) and (Wan et al., 2018). All the approaches proposed quantify resilience from one or both of the following two perspectives:

1) The ability to maintain functionality under disruptions, and
2) Time and resources required to restore performance levels after disruptions.

The first perspective relates to the performance loss during the response and recovery phases, from the happening of the disruption the moment in which performance returns to an equilibrium condition. It refers to the area between the undisrupted and disrupted curve, as shown in Figure. The second perspective relates to the recovery phase, considering both the time and resources necessary to restore the initial functionality.

(Bruneau et al., 2003) introduce the concept of "*resilience triangle*", illustrated in figure. The triangle includes both the robustness against the initial performance loss and the rapidity of the recovery process. They propose a deterministic static metric for evaluating the resilience loss (*RL*) of a community infrastructure in the aftermath of an earthquake:

$$RL = \int_{t0}^{t1} [100 - Q(t)]dt \qquad \text{(Eq. 2.1)}$$

Where *Q(t)* denotes the quality of the infrastructure at time t, where quality could represent several kinds of performance measures, such as the reduction in power supply for an electric power system. This metric quantifies the area of the resilience triangle, dashed in figure, and larger values indicate lower resilience values, and vice versa.

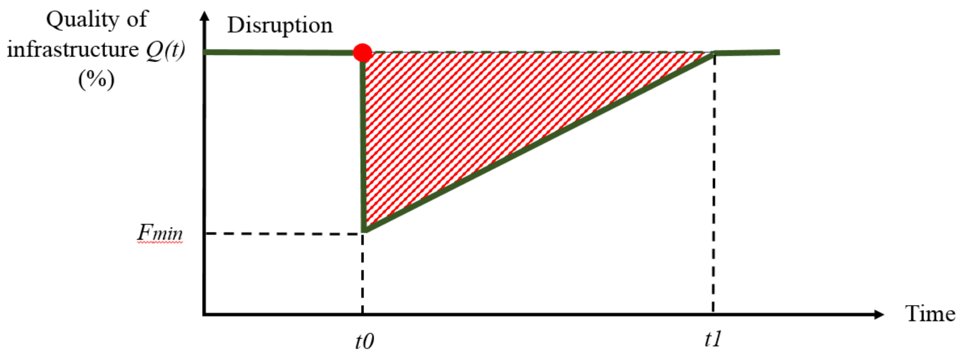


Figure 2.5. The resilience triangle proposed in (Bruneau et al., 2003)

(Henry & Emmanuel Ramirez-Marquez, 2012) propose a resilience metric as a time dependent function. The proposed metric considers system resilience as an attribute of a system's delivery function. It describes how the system delivery function changes in face of a disruptive event and how the system returns to the normal state from such distress state. Given the performance of the system at a point in time *φ(t)*, the resilience Я is evaluated as the ratio of recovery up to time *t* to the loss suffered by the system:

$$Я_{\varphi}\left(t\middle|e^{j}\right) = \frac{\varphi\left(t\middle|e^{j}\right) - \varphi\left(t_{d}\middle|e^{j}\right)}{\varphi(t_{0}) - \varphi\left(t_{d}\middle|e^{j}\right)} \quad \text{(Eq. 2.2)}$$

Where the disruption starts at time t_0, ends time t_e and causes performance degradation until time t_d. They apply their methodology to an illustrative example where loss is evaluated in terms of increased shortest path length, number of trips per day, overall health of the network. They also calculate the total cost of recovered systems as sum of the loss cost due to the inoperability of the disrupted system and the cost for resilience actions.

(Enjalbert & Vanderhaegen, 2017) introduce a local and global resilience indicator, in the context of public transportation systems from a safety management perspective, defined as:

$$global\ resilience = \int_{tb}^{te} local\ resilience = \int_{tb}^{te} \frac{dS(t)}{dt} \quad \text{(Eq. 2.3)}$$

Where t_b and t_e are the times when the disturbance effects start and finish, respectively. S(t) is a safety indicator measured as the sum of the effects of those factors which can affect system's safety.

(Vugrin et al., 2010) develop a mathematical resilience cost measurement approach to determine the impacts of disruptions and the resilience costs associated with disruptions. their approach requires the quantitative definition of two indicators:

1) the Systemic Impact (*SI*), which is the impact on systems' productivity; it is evaluated as the difference between a targeted system performance and the actual one, following a disruption;
2) the Total Recovery Effort (*TRE*), which refers to the efficiency with which the system recovers from a disruption, is measured as a function of the amount of resources expended during the recovery process.

Resilience is then computed as a linear combination of *SI* and *TRE*, normalized through the total performance loss.

In (Orwin & Wardle, 2004), a measurement metric is proposed which links the resilience with instantaneous and maximum disturbance:

$$Resilience = \left(\frac{2 * \ |E_{max}|}{|E_{max}| + |E_j|}\right) - 1 \qquad \text{(Eq. 2.4)}$$

where E_{max} is refers to the maximum intensity of absorbable force without perturbing the system functioning, and E_j refers to the magnitude of the disturbance's effect at time T_j. The highest resilience is obtained when $E_j=0$, i.e. when the impact is fully recovered. A limitation of this approach is that, as it does not consider the time to recover, two systems with different recovery times could have the same resilience value.

In (Chen & Miller-Hooks, 2012), a different indicator is introduced in the context of transport systems. Resilience R is quantified as the expected fraction of demand that can be satisfied in the post-disaster network by using specific recovery costs:

$$R = E\left(\sum_{\omega\in W} d_\omega \Big/ \sum_{\omega\in W} D_\omega\right) = \frac{1}{\sum_{\omega\in W} D_\omega} E\left(\sum_{\omega\in W} d_\omega\right) \qquad \text{(Eq. 2.5)}$$

Where parameter d_ω is the maximum demand satisfied for origin-destination pair ω in the post-disaster network, and D_ω represents the satisfied demand for origin-destination pair ω in the pre-disaster network.

(Francis & Bekera, 2014) propose a metric which, in addition to previous ones, incorporates also the recovery aspect. They incorporate the three resilience capacities (absorptive, adaptive and restorative). The absorptive capacity is expressed as the proportion of the original functionality maintained at the end of the recovery phase: F_0 / F_r, where F_0 and F_r are, respectively, the initial and recovered performance levels. In order to describe the adaptive capacity, the authors suggest the ratio F_d / F_0, which represents the capability of a system to absorb shocks without recovery action, and where F_d is the performance immediately after the disruption. The restorative capacity is incorporate in the factor S_p. then, resilience ρ for event i is evaluated as:

$$\rho_i = S_p \frac{F_r}{F_0} \frac{F_d}{F_0} \qquad \text{(Eq. 2.6)}$$

(Chang & Shinozuka, 2004) propose a probabilistic approach to evaluate resilience, where resilience is measured combining two elements: loss of performance and length of recovery. Resilience is then defined as:

$$R = P(A|i) = P(r_0 < r^* \; and \; t_1 < t^*) \qquad \text{(Eq. 2.7)}$$

That is the probability of the initial performance loss to be under the maximum acceptable loss r^* and the time to fully recover to be shorter than the maximum acceptable disruption time t^*.

(Youn et al., 2011) defined resilience ψ including mitigation and contingency strategies. They interpret resilience as the sum of the passive survival rate (reliability) and an active response (restoration):

$$\psi = R \; (reliability) + \rho(restoration) \qquad \text{(Eq. 2.8)}$$

Restoration is defined to be the degree of reliability recovery and is calculated as the joint probability of a system failure event, a correct diagnosis event, a correct prognosis event and a successive recovery action event. Differently from other works, this indicator account for reliability, which can be intended a part of the anticipation capacity of resilience.

Several other indicators have been proposed in literature, similar to the ones mentioned above. A comprehensive review of resilience metrics can be found in (Hosseini et al., 2016), where such indicators are divided in deterministic and stochastic measures, each of which have been used to describe static or dynamic system behaviour. On one hand, uncertainty (e.g. probability of disruption) is not included into the metric in a deterministic performance-based approach; on the other hand, a probabilistic performance-based approach incorporates the stochasticity associated with system behaviour. Moreover, resilience metrics can be static, i.e. resilience measures do not depend on time, or dynamic, meaning that the time-dependent behaviour of the system is considered. In the following, the principal metrics used will be described.

From the definitions illustrated above and reviews, several comments can be drawn. First, also from a quantitative point of view, there is no agreeably accepted metric of resilience; this comes as a consequence of the fact that no consistent interpretation of resilience exists yet. Furthermore, the various different quantitative interpretations reflect the multiple aspects included in the concept of resilience. Each metric focuses on one aspect rather than others, many studies evaluate one or more resilience capacities, but no one includes them all in a comprehensive metric. In addition, the quantitative approaches available are quite specific and limited to the case for which they have been developed. Different disruptions may hurt the system in different ways, thus requiring different recovery actions. Moreover, the response strictly depends on the structure of the system.

2.4. Resilience, robustness and vulnerability

The term resilience has been often erroneously confused with tightly connected concepts (Faturechi & Miller-Hooks, 2015). In particular, a high degree of ambiguity exists in literature between the words "*resilience*", "*robustness*" and "*vulnerability*". In the remaining of Section 2.4, a differentiation between these three terms is provided.

2.4.1. Resilience and robustness

In several different domains, the relation between resilience and robustness has been discussed many times and, according to some authors, it can be stated that "ecological resilience" tends semantically to robustness (Brand & Jax, 2007; Gluchshenko & Foerster, 2013; Woods, 2015). According to the Oxford dictionary (Stevenson, 2011), an object (system or organization) is robust if it is "*able to withstand or overcome adverse conditions*". (Gluchshenko, 2012) defines system's robustness as "*the ability to experience no stress since a disturbance has occurred".* Thus, a system is robust against a disturbance if it is remains within the boundaries of the reference state for a particular period of time. A robust behaviour is relative to a specific disturbance and to a particular reference state of a system. Differently, a resilient behaviour exhibits if the state of the system crosses the boundaries of its domain. However, both concepts are defined by a performance reference state, a particular disturbance and a particular period of time. Robustness is a property which can increase system resilience. In fact, enhancements in system robustness decrease the impact of a disruption, thus contributing to the absorptive capacity of the system. Figure 2.6 illustrates the case of a disturbance which causes the degradation of the performance of a system. A system is robust (Figure 2.6b) if the stress remains within the boundaries of the reference state during the perturbation time.

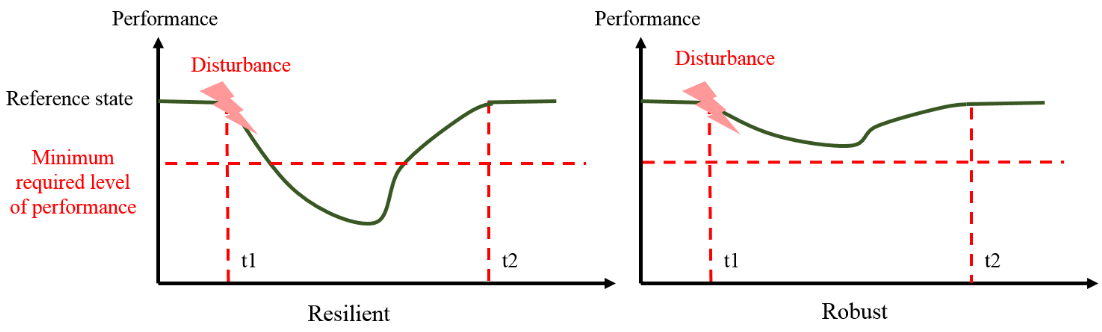


Figure 2.6. (a) Resilient and (b) robust behaviour of a system affected by a disturbance

2.4.2. Resilience and vulnerability

Parallelly to the recent increasing interest in resilience, also the concept of vulnerability recently attracted a growing attention in a wide range of different domains, including natural hazard and climate change (Neil Adger, 1999), psychology (Riskind & Black, 2006) and transportation (Berdica, 2002). Similar to resilience, also the concept of vulnerability has been largely discussed and several definitions and measures have been formulated to describe it, without reaching an unambiguous conclusion. What is clear is that both resilience and vulnerability represent two related yet different approaches to understand the response of systems to disruptions.

The word "vulnerability" is used in every-day language to express the sensitivity to attacks or injuries. In the context of socio-technical systems, the term ''vulnerability'' refers to the susceptibility of a system to experience severe performance impacts in consequence of exceptional disruptions (Mattsson & Jenelius, 2015; Malandri et al., 2018). (Haimes, 2009) offered the following definition of vulnerability: "*Vulnerability refers to the inherent states of a given system (e.g. physical, technical, organizational and cultural) that can be exploited by an adversary to adversely affect (cause harm or damage to) that system*". According to, vulnerability refers also the speed of the degradation of its performance (Wan et al., 2018). This definition emphasizes that there is an initial disruptive event, which affects the system ability to provide services to the users and that results in relevant adverse consequences. In a similar way, (Mattsson & Jenelius, 2015) define vulnerability as "*society's risk of transport disruptions and degradations*".

Both vulnerability and resilience represent the capability of a system to withstand threats and, in principle, they were considered to be two sides of the same coin, vulnerability having a more negative connotation. However, recently some authors questioned this definition arguing that they refer to two slightly different features, and it would be a drastic simplification to treat resilience only as the opposite of vulnerability (Seeliger & Turok, 2013). In fact, vulnerability refer to the performance degradation of a system when affected by specific types of specific types and levels of magnitude of threats. However, vulnerability does not provide information about the recovery capacity of the system, while, on the other side, resilience also represents the ability of the system to return to the normal state within an acceptable time, costs and risks, having being presented a shock. Vulnerability can be considered as a part of resilience, namely the converse of the absorptive capacity, as shown in Figure 2.7. Referring to the framework proposed by (Hollnagel, 2016), it can be stated that vulnerability mainly deals with the resilience ability to "know what to expect" (Mattsson & Jenelius, 2015).

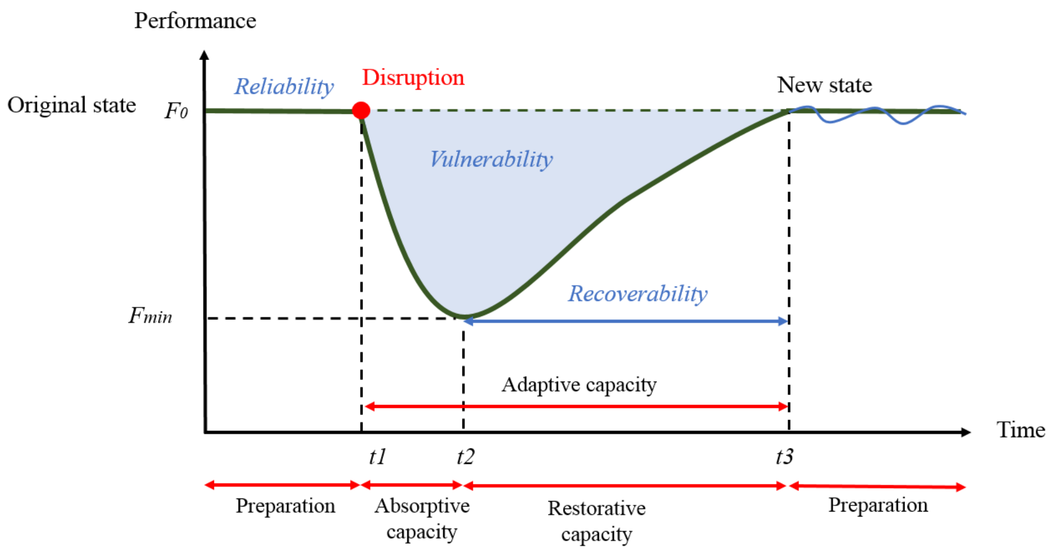


Figure 2.7. System performance during a disruption to describe vulnerability

2.5. Summary

In this Chapter, the topic of resilience has been introduced and the background context described. Research on resilience has gathered considerable momentum in the last years. Originally emerged in the context of materials' testing, the concept of *resilience* generated interest in numerous scientific communities and is nowadays studied in a plethora of fields.

With the increased popularity of the topic, also confusion has grown about the meaning of the term: several definitions have been proposed and the label "*resilience*" has been used in multiple different ways. What is common to all definitions, is that the general use of this word indicates the desirable ability of a system or entity to withstand events that disrupt its state, and to return to normal conditions after the occurrence such disruptions. However, it is not unambiguously clear how the concept of resilience is defined, and in recent years the need has arisen for an agreed and clear definition, as well as for quantitative metrics to evaluate it.

In the context of socio-technical systems – such as air transportation - what emerges is that resilience is a conceptual framework composed of multiple dimensions. Recently, literature seems to converge towards the fact that a resilient system should have four main properties to respond to perceived or real shocks, in order to maintain its original functionality. These properties, denoted with the term "*resilience capacities*", are:

- preparation: the ability to anticipate and be prepared to potential threats;
- absorptive capacity: the degree to which a system can adsorb disruptions' impacts;
- adaptive capacity: the ability of a system to re-organize itself;
- restorative capacities: the ability of a system to return to pre-disruption performance.

Some indices have been proposed which focus on one or more of such aspects of resilience, such as the recovery time or the performance loss in the wake of the disruption. However, a holistic quantitative metric or approach to include all these capacities is still missing, and more efforts are still required and hoped-for to establish a comprehensive framework.

Moreover, the term resilience has been often erroneously confused with tightly connected concepts, thus increasing the confusion surrounding the topic. In particular, a high degree of ambiguity exists in literature between the words "*resilience*", "*robustness*" and "*vulnerability*", which however refer to different but cognate concepts. The term robustness indicates the ability to experience no stress since a disturbance has occurred. Thus, a system is robust against a disturbance if it is remains within the boundaries of the reference state for a particular period of time. Differently, a resilient behaviour exhibits if the state of the system crosses the boundaries of its domain. Regarding the concept of vulnerability, it refers to the susceptibility of a system to experience severe performance impacts in consequence of exceptional disruptions. Then, vulnerability does not provide information about the recovery capacity of the system, while, on the other side, resilience also represents the ability of the system to return to the normal state within an acceptable time, costs and risks, having being presented a shock. Thus, vulnerability can be considered as a part of resilience, namely the converse of the absorptive capacity, and this is the interpretation that will be used in the remaining of this thesis. As a result, when talking of resilience, vulnerability is also taken into consideration. From the next section on, the focus will be directed to transportation systems, and in particular air transportation.

3. LITERATURE REVIEW

3.1. Transportation and resilience

The well-functioning of societies largely relies upon a quantity of strategically critical infrastructure systems, which are defined by the European Commission as "*an asset or system which is essential for the maintenance of vital societal functions*" (European Commission, 2018). They include, among other, water supply systems, electrical grids, communication and information networks, infrastructures and transportation. In the past decades, these systems have become gradually more complex and interdependent, which makes them more vulnerable to disruptions and difficult to recover. If one of these systems is damaged or disrupted, society can suffer extremely severe consequences in terms of economic and social losses.

For this reason, the last years were disseminated by efforts to identify and minimize the impacts caused by critical infrastructure disruptions. For example, the European Commission states that "*reducing the vulnerabilities of critical infrastructure and increasing their resilience is one of the major objectives of the EU*" (European Commission, 2018). The interested in the resilience and vulnerability of critical infrastructures systems in the face of disruptive events and resulting consequences have awakened increasingly interest among researchers and planners, especially after the events of September 11, 2001 (Haimes et al., 2008).

This is especially relevant for transportation systems, which is one of those critical infrastructure systems and it is vital for the safety and functioning of societies in developed and developing countries; moreover, transportation networks provide access to impacted areas supporting emergency response and long-term recovery after a disaster. For these reasons, the efficient functionality of transportation systems is significative from both economic and welfare perspectives.

Transportation systems are often subject to disruptions, ranging from more common failures to large scale natural disasters, which are becoming more frequent as well as impactful. Natural disasters, including earthquakes, volcanoes eruptions and hurricanes, are the main causes of large-scale transportation disruptions, for example the Hurricane Katrina (2005), Tohoku earthquake and tsunami, and others. Moreover, the disruptive events usually affecting transport networks can be particularly bad weather (fog, heavy snowfall or rain), strikes of the transport staff, traffic incidents and terroristic attacks. Disruptive events may be more or less predictable and, sometimes, they can occur simultaneously and be interrelated. Stakeholders more likely to be affected are usually the network operators (providers of transport services), their users (passengers) and goods receivers: when the service deteriorates, they are all usually imposed additional costs.

(Murray-Tuite, 2006) is the first work which addresses explicitly the concept of resilience in the context of transportation systems, and not simply referring to general infrastructures. In his study, she affirms that transportation resilience has ten dimensions, namely redundancy, diversity, efficiency, autonomous components, strength, collaboration, adaptability, mobility, safety and the ability to recover quickly.

Then, the literature related to resilience in the context of transport area has grown particularly, even if definitely more attention has been paid to vulnerability rather than resilience in transport networks. A plethora of studies have been conducted on transport resilience, focusing on different transportation modes, such as roadways (Jenelius & Mattsson, 2012), public (Malandri et al., 2017), freight (Chen & Miller-Hooks, 2012), maritime (Baroud et al., 2014), railway (Adjetey-Bahun et al., 2016) transportation systems. A recent review by (Zhou et al., 2019) shows that, up to 2018, the road network is the most studied transportation mode, (44%), followed by freight transportation (13%) and railway and metro systems (12%). Only a few focuses on maritime and air systems (8% each) and multi-modal transportation network (6%). Some works address the topic for a general transportation network (6%).

Even if there is no universal description on what transportation resilience should be, the definitions of resilience given in the different transportation modes share the same underlying ideas, with some differences related to the characteristics of the specific transportation mode. Most of these studies determine resilience by considering one or both of the following aspects: system performance under abnormal conditions, and the speed and resources required for recovery to original functional states.

To summarize the large amount of works dealing with this topic, some review articles have been published recently. A careful review of definitions is given in (Zhou et al., 2019). (Mattsson & Jenelius, 2015) and (Reggiani et al., 2015) put the emphasis on the relation between vulnerability and resilience. (Faturechi & Miller-Hooks, 2015) classified and analysed frequently used performance metrics for transportation disasters including resilience.

According to (Reggiani et al., 2015) categorize approaches to resilience in general or specific. A general approach can easily be replicated in various context; in most cases, studies adopting such a framework usually stay in the domain of complex networks. A specific approach belongs to a specific empirical context, e.g. road network infrastructures or air transport network.

According to (Mattsson & Jenelius, 2015), in the increasing literature on transport resilience and vulnerability, two distinct approach traditions can be identified. The first one could be characterized as topological analysis and has its roots in graph theory. Transport network resilience and vulnerability have been often studied in terms of network topology; in these studies, the transport system is represented as an abstract graph where nodes, corresponding for example to stations or stops, are connected by links which represent roads or service segments (Berche et al., 2009; Von Ferber et al., 2009). The network could be directed or undirected, weighted or unweighted. The distance between any two pairs of nodes is defined as the shortest distance among all possible routes between the nodes.

Disruptions are then simulated by removing graph's elements (nodes or links) randomly or by means of ''directed attacks'', i.e. selecting and deactivating links or nodes according to different centrality measures, such as the highest degree or betweenness centrality (Holme et al., 2002). After each removal, resilience or vulnerability are evaluated in terms of the decrease in network's performance, measured as the change of some selected topological and connectivity properties. Topological metrics used to evaluate the change in performance are, for example, average shortest paths and size of the giant component (Berche et al., 2009), betweenness centrality and network diameter (Aydin et al., 2018), network efficiency (Latora & Marchiori, 2001), average node degree (Zhang et al., 2015), clustering coefficient and redundancy (Testa et al., 2015). Although these metrics are defined in different ways, most of them compare the structure of the transportation network with the corresponding complete graph.

The analysis of transport network resilience by using a strictly topological approach is very efficient, however it has considerable shortcomings. Such studies neglect a large number of factors, most importantly the interaction between supply and demand and their inherent stochastic processes are not captured in these models. Topological studies effectively assume that the removal of a link is equivalent to the network without this link to start with, with the remaining segments supposed to continue functioning independently. However, unplanned disruptions can cause adverse effects because service providers and users cannot adjust to them upfront (Malandri et al., 2018). Travel demand and in particular the effect on passenger rerouting and the number of affected users need to be explicitly considered. Moreover, the dynamics of transport system lead to the propagation of disturbances across the network due to knock-down effects on infrastructure and rolling stock and spill-over effects due to the redistribution of travellers’ flows and capacity limitations.

To overcome these limitations, recently some studies have been proposed which model the interaction between supply and demand, allowing the evaluation of additional important factors such as the level of congestion and delays (Cats et al., 2016; Rodríguez-Núñez & García-Palomares, 2014). This second tradition, which could be called system-based analysis of transport networks, represents much more of the structure of the real transport system in the demand and supply models that are applied in the analysis. In this works, resilience metrics considers both structures of transportation systems and the traffic flow on them. (Zhou et al., 2019) classify such metrics in attribute-based and performance-based.

Generally, attribute-based metrics attempt to measure one or more properties of resilience transportation systems, i.e. robustness, redundancy, resourcefulness and rapidity (Bruneau et al., 2003), by evaluating the performance at specific periods. Most of them concentrate on the recovery phase and two principal metrics are used: recovery time - i.e. the time required for the system to return to an equilibrium state - and recovery efficiency, which includes the resources required for the recovery. The metrics used in literature include, among the others, the ratio between disrupted travel time and travel time in undisrupted conditions (Beiler et al., 2013), unaffected passenger flow (Hua & Ong, 2017), redundancy, i.e. availability of alternative routes (Yoo & Yeo, 2016).

On the other side, performance-based metrics try to asses system’s resilience in a more comprehensive way. Differently from attribute-metrics, they are designed to measure system’s resilience based on their performance over the whole period affected by disasters. The most widely used performance-based metrics are:

1) Degradation of system quality over time, in accordance with the definition proposed in (Bruneau et al., 2003) and mathematically formulated by means of Equation 2.1. The performance loss is evaluated by considering different indicators: for example, in (Bocchini et al., 2014), the quality of the system is quantified by means of a performance metric based on total travel time and total travel distance (Adjetey-Bahun et al., 2016); quantify the resilience of railway systems is evaluated in terms of passenger load and passenger delay; in the context of road and subway systems affected by hurricanes, (Zhu et al., 2016) evaluate the quality of the system as a function of the percentage of evacuees leaving the risk area by time.

2) Time-dependent ratio of recovery over loss, following the definition given by (Henry & Emmanuel Ramirez-Marquez, 2012) and described in Equation 2.2. This metric was used to study the resilience of inland waterway network (Baroud et al., 2014), marine transportation systems (Farhadi et al., 2016) and urban transportation (Liao et al., 2018).

3) The third performance-based indicator was proposed by (Chen & Miller-Hooks, 2012) in the context of freight transportation systems. Resilience is defined as in Eq. 2.5 as the expected fraction of demand satisfied by the post-disaster network using specific recovery costs. This indicator was adopted in several studies in order to study, among the others, the resilience of metro networks (Jin et al., 2014), roadway networks (Faturechi & Miller-Hooks, 2014), air transport networks (Janić, 2015).

Moreover, different measurement approaches have been used to provide the performance assessment of transportation systems for the calculation of resilience metrics. According to (Zhou et al., 2019), these approaches can be categorized in optimization models (Bocchini et al., 2014; Faturechi et al., 2014), topological models (Berche et al., 2009; Dunn & Wilkinson, 2016), simulation models (Murray-Tuite, 2006; Osei-Asamoah & Lownes, 2014), probability theory models (Baroud et al., 2014; Hosseini & Barker, 2016), fuzzy logic models (Freckleton et al., 2012), and data-driven models (Belkoura et al., 2016; D'Lima & Medda, 2015).

3.2. Resilience and vulnerability of air transport systems

Despite the large amount of works published in various domains regarding the concept of resilience, and in particular regarding the transportation field, the number of studies related to air transportation is quite limited in number.

The air transport system is a complex socio-technical system in which a large number of elements – both human and technological – interact with each other and work together (O'Regan, 2011). In this complex system, different stakeholders interact at different levels. Specifically, the air transport system can be decomposed in three main layers: network, airlines and airports. Disruptions may affect the air transport system's performance at one or more of these layers, and thus resilience could be evaluated at each of these levels.

In literature, air transport resilience studies mainly focus on the efficiency of the network as a whole, or of a part of it. There are handful of works which focus on the operations of individual carriers, or of alliances of airlines. Whilst, only few studies use measures to consider the resilience at the individual airport level.

In this section, a comprehensive review of recent studied addressing the topic of resilience in air transportation systems is presented, comprehending published paper from 2005 to 2019. Are included in the analysis also the works dealing with vulnerability and robustness of air transport networks. This choice comes with the fact that vulnerability can be considered as a component of resilient, specifically referred to the absorptive capacity of resilience. Moreover, in many works, the distinction between vulnerability and robustness is not clear, and the two terms are often used interchangeably.

The works are divided in three categories, depending on the level considered: network (Section 3.2.1), airline (Section 3.2.2) or airport (Section 3.2.3). Moreover, some papers refer to resilience in the ATM (Air Transport Management) context (Section 3.2.4). A summary of the papers reviewed in given in Table 3.1. In the table, for each study it is specified the topic analysed (resilience, vulnerability or robustness); the level of analysis (airport, network, airline, ATM); the approach adopted (topological or system-based), in accordance with the description given in the previous Section 3.1; the resilience capacity discussed and the indicators used to quantify it.

As a result of the review, it emerges that most of the research efforts concentrates on determining the resilience of air transport network in general (49%, see figure 3.1). Among those, only a few studies adopt a system-based approach, while the others base on complex network theory to deduct topological properties of the network. In the remaining studies, attempts are made to determine the resilience at the airline, or alliances, level (21%) and at the airport level (13%). In the latter group, only system-based approaches are adopted.

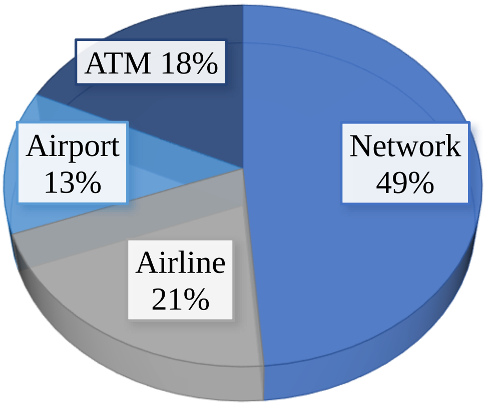


Figure 3.1. Level of analysis of studies related to air transport resilience

3.2.1. Air network level

The majority of studies related to resilience and vulnerability in the context of air transportation analyse the network as a whole. These studies generally adopt a topological approach and use graph theory to describe the topology of the network, before and after a disruption. Nodes represent airports and links between two nodes is created whenever it exists a direct flight between the two airports associated with the node. The network is naturally a directed graph where a link represents flights from the first node to the second one. Links are typically weighted, and the weight may be determined by considering the number of flights present between the two airports in the examined period of time, or otherwise evaluated in terms of number of air travellers on the link. Then, a disruption is simulated by removing nodes (closed airports) or links (closed routes) randomly or by following pre-determined "attack" strategies, for example by eliminating the most central nodes. Resilience and vulnerability are then evaluated by comparing diverse topological measures, such as connectivity measures, clustering coefficient, edge betweenness, and especially the size of the largest connected component, which is the most widely used. This methodology has been applied to several air traffic networks, including the European, Chinese, US, and others.

For example, (Hossain et al., 2013) present a complex network approach for measuring the performance and estimating the resilience of an airport network, using the Australian Airports Network (AAN) as a case study. They remove central and random nodes, while links are removed randomly. Resilience is evaluated as a function of the average inverse geodetic length and of the connectivity between any pair on nodes.

The topology of the Chinese airport network (CAN) is studied in (Li et al., 2014), where resilience is evaluated against attacks by comparing changes in static properties such as the clustering coefficient, network diameter and efficiency. Similarly, (Agrawal et al., 2015) propose a graph analysis approach to identify the robustness of Indian Airport Network, considering the size of the largest connected component.

Also the U.S. airport network has been widely analysed. (Yoo & Yeo, 2016) evaluate the resilience of the US air transportation network as the ability of an attacked node to be replaced by an adjacent node, thus analysing the redundancy of the network. In this study, based on percolation theory, the degree of adaptation is determined as the number of nodes required to replace the flow of the removed node. The cost of adaptation depends on the total distance of redistributed flights. (Cerqueti et al., 2019) consider resilience of an air network as its ability to absorb a shock. They study shock propagation along the patterns of connections among nodes, which is assumed to strongly depend on the weight of the arcs. Resilience is conceptualized as a weighted combination of the cardinality of the sets collecting the paths with different length. They test the proposed measure of resilience on two empirical networks extracted from the network US commercial airports. The U.S. airport network is studied also in (Clark et al., 2018), where it is evaluated the resilience of the network to perturbations localized on nodes (airports). The size of the giant component is chosen as variable of interest. With a methodology based on percolation theory, airports fully recover progressively with a priority list of restoration depending on various flow and topological metrics, including traffic volume, connectivity and network centrality measures. (Thompson & Tran, 2018, 2019) present a defender-attacker-defender model to analyse the potential impacts of intelligent attacks and worst-case disruptions on the U.S. air transportation network. The two metrics of interest are the number of potentially impacted travellers for each of the attack scenarios, and how it is effective to increase the defence budget to reduce that impact. (Chandramouleeswaran & Tran, 2018) present a data-driven approach for quantifying the resilience on the US air transportation network using publicly available data. The methodology relies on a statistical measure, the Mahalaobis distance, to detect atypical behaviour in the network. The parameters of interest are the total cancellations and average flight delays across all airports.

In (Kim & Yoon, 2019), the air route network robustness of the Northeast Asia region is assessed, based on node criticality. Three variations of network are considered, namely unweighted, distance-weighted and demand-weighted. Two measures of vulnerability are proposed: (i) the relative size of the largest component, representing cohesiveness in terms of connectivity, and (ii) the number of operable flights, representing the sustainability of flight operations in disrupted airspace.

The work by (Sun et al., 2017) investigates the robustness global air transportation from a complex point of view. They apply different attacking strategies – degree, betweenness, closeness, eigenvector, Bonacich and damage targeted attacks - and measure robustness in terms of survived links, giant component. Moreover, they propose a novel notion of functional robustness which depends on the number of unaffected passengers with rerouting. (Yan et al., 2013) analyse the vulnerability of an air transportation network with 160 destinations by means of a normalized average edge betweenness and a multi-scale average edge betweenness. (Lordan et al., 2014) present a methodology for the detection of critical airports in the worldwide airport network, and network robustness is measured as the size of the giant component. In a related paper, (Soria et al., 2017) extend the definition of the air route network robustness by testing several heuristics to define selection criteria to detect critical nodes. Again, they analyse the evolution of the size of the component. (Roy et al., 2017) propose a flow-vulnerability metric for the air transportation system, using the Laplacian matrix of the air traffic network's graph.

Differently from previous mentioned works, (Wilkinson et al., 2012) investigate spatially coherent hazards affecting the European Air Traffic Network. The aim of their work is to evaluate whether the eruption of Eyjafjallajokull volcano in 2010 had a disproportionate effect on the European Air Transport Network. The network was constructed by acquiring data regarding airport's location and air routes. They simulate a spatially coherent disruption which change over time and lasts for more than one day. Vulnerability is evaluated by plotting the number of cancelled routes relative to the proportion of closed airspace, demonstrating that the European air transport network is vulnerable to spatial hazard. In a following work, (Dunn & Wilkinson, 2016) assess two strategies to improve the resilience of air traffic networks when subjected to a spatial hazard. One strategy "adaptively" modifies the topology of the network, the other "permanently" modifies the topology. They quantify the ability of these two strategies to increase the resilience of the European air transport network by considering the same indicator used in the previous work, i.e. by plotting the proportion of cancelled air routes against the proportion of closed airports. The consequences of the eruption of the Eyjafjallajökull volcano are discussed also in (Reichardt et al., 2018, 2019), where the authors debate with aviation experts about crisis scenarios in case of volcanic ashes, as the event in 2010 demonstrated that ash from volcanic eruptions can severely interrupt air traffic. The aim is to identify opportunities for improvement of responses. Inspired by the work in (Wilkinson et al., 2012), (Li et al., 2016) propose a new spatial vulnerability model which considers hazard location and area covered by the hazard. They propose an absolute and a relative spatial vulnerability index, which depends on the area covered by the hazard and the effective impacted node.

In (Cardillo et al., 2013), a multiplex formalism is introduced, i.e. the European Air Transport Network (EATN) is modelled by considering flights operated by each airline as an independent network, in order to take into account for the presence of interactions at multiple levels which may negatively affect the resilience of the system. They analyse the resilience of the system in the passengers' rescheduling process as a function of the probability of a link to be deleted and the fraction of tolerance that airlines assign to their connections.

The examples of air transport resilience analysis based on a system-based approach are very limited. One example is the one provided in (Voltes-Dorta et al., 2017b), where the authors analyse the vulnerability of the European air transport network to major airport closures from the delays imposed to disrupted airline passengers. Passengers are re-located to minimum-delay itineraries and aggregate delays are used to rank the criticality of each airport to the network.

Another interested work is the one presented in (Janić, 2015). The aim of such work is to determine the resilience and friability of a given air transport network affected by a large-scale event. Friability implies reducing the network's existing resilience due to removing specific airports or air routes. Here, resilience is intended as "*the ability to withstand and stay operational … during the impact of a disruptive event*" and a resilience metric is proposed defined which takes into consideration the on-time flights as a proportion of the scheduled flights. The methodology is applicated to the U.S. transport network during Hurricane Sandy, in October 2012.

3.2.2. Airline level

While the preponderance of works analyses the resilience of the global air network, there is a handful of studies which focus, rather than on the functioning of the air traffic network as a whole, on the resilience of individual air carriers or, in some cases, alliances of airlines. Also at the airline level, almost all works adopt a topological approach.

For example, (Wuellner et al., 2010) analyse the individual structures of the seven largest passenger carriers in the USA (by number of passengers flown). They examine the individual passenger carrier's resilience to random edge removal. Edges are weighted with the total number of flights flown between the airports (nodes) connected and network's performance is quantified as the size of the largest connected component and as a function of a global travel cost metric. They found out that networks with high interconnectivity are extremely resilient to both targeted removal of airports (nodes) and random removal of flight paths (edges); such networks stay connected and incur minimal increase in a heuristic travel time. in addition, they proposed rewiring schemes to enhance network resilience. (Sun & Wandelt, 2017) investigate the robustness of 24 Chinese airline networks under disruptions at their critical airports, i.e. its own dominating hub. Again, the robustness is evaluated in terms of the size of the giant component of the network. Similarly, the size of the giant component is used as robustness indicator also in (Lordan et al., 2016), where the topological robustness of individual airline networks are examined. They found out that the point-to-point flight networks of LCCs (*low-cost carriers*) are more robust than the hub-and-spoke structures of traditional carriers.

Instead, (Klophaus & Lordan, 2018) apply complex network theory to measure the vulnerability of the code-sharing network of *Star Alliance*, *SkyTeam* and *Oneworld*, respectively, to (potential) member exists. Vulnerability is measured using the concept of normalized average edge betweenness. In a similar work, (Lordan et al., 2015) also introduce an inverted adaptive strategy based on the network efficiency.

Differently from the above mentioned works, (Janić, 2005) adopt a system-based approach to assessment of the economic consequences of large-scale disruptions of an airline single hub-and-spoke network. He develops a model based on the theory of queuing systems in which the airline is the server, and the complexes of flights are customers. Consequences are expressed by the cost of delayed and cancelled complexes of flights. The same author, a few years later, models the resilience of an airline cargo network affected by a large scale disruptive event (Janić, 2019). A resilience index is defined as the average ratio of the area between the deteriorated curve and the area below the regular curve. The metric is adapted by the one formulated in (Chen & Miller-Hooks, 2012) (see Eq. 2.5). The resilience index is then evaluated for different performance indicators, as the author assumes that the different indicators of performance are differently sensitive to the impact of a given disruptive event. Specifically, the indicators of performance considered are the number of airline flights, the transport work, the airline profits, the value of time of air cargo shipments and the inventory cost of air cargo shipments. Another example of system-based approach can be found in (Asgary et al., 2016), where agent-based simulation is applied to analyse the impact of airport closures on an airline route network, and different scenarios are simulated with different disruption durations. The model provides information about delayed and cancelled flights and passengers.

3.2.3. Airport level

In literature, also studies related to single airports' resilience can be found, even if such works are very limited in number. In this case, analyses are mostly conducted by adopting a system-based approach: airport operations are modelled in a more or less comprehensive way and, in many cases, disruptions are simulated by means of simulation software.

(Marzuoli, Boidot, Feron, et al., 2016) provide a case report for the Asiana crash in San Francisco International Airport in 2013 and analyse its repercussions on the multimodal transportation network in terms of delayed, diverted and cancelled flights. In a related work (Marzuoli, Boidot, Colomar, et al., 2016) the goal of the paper is to examine how to support better crisis management at the network level, from passenger-centric and flight-centric perspectives. They tackle mitigation strategies following the Asiana crash.

(Voltes-Dorta et al., 2017a) analyse the ability of a tourism-oriented airport (Palma de Mallorca airport) to relocate departing passengers in the event of an unexpected airport closure. Passengers are relocated to minimum-delay itineraries. Aggregate delays and relocation rates are used to assess the impact of each scenario.

In (Malandri et al., 2017), resilience aspects of transit systems accessing airport areas are discussed. They estimate the impacts produced by unplanned disruptions of transit systems serving an airport as a function of the system recovery time and increase in generalized travel cost.

(Pejovic et al., 2009) identifies the vulnerabilities of operations at Heathrow airport to a short airport closure. The consequences of the disruption on system's performance are assessed in terms of delays, flight rerouting and diversions to alternate airports, and flight cancellations. They also measure the impact in terms of CO_2 emissions, by using the RAMS Plus simulator. A cost assessment is performed based on the average costs of air traffic delays, flight cancellation and diverted, estimated by EUROCONTROL.

Lastly, in a recent interesting paper, (Damgacioglu et al., 2018) define resilience as an airport's ability to maintain an operational level as close to normal as possible during and immediately after the occurrence of a disruptive event. They develop a route-based simulation framework in order to analyse the adversarial impact of such disruptive events on an airport ground system. The model is implemented by using the programming language MATLAB. Two disruptive events, namely taxiway pavement damage and runway closure, are investigated in terms of their impact on taxi-in and taxi-out times for the case of LaGuardia airport ground system. Alternative strategies to reduce such flight delays under those events are investigated.

3.2.4. ATM level

In addition to the works mentioned above, some research efforts have been dedicated to the analysis of resilience in the ATM (Air Traffic Management) context. The ATM domain is an instance of a complex socio-technical system in which people must cooperate with each other and with technologies in order to achieve their goals. Given the complexity of the system, a system-based approach is required to include all principal aspects and stakeholders in the analysis.

In a conceptual paper, (Gluchshenko & Foerster, 2013) present a framework that incorporates concepts of resilience and robustness, stress and perturbation. They suggest some qualitative and quantitative measures of resilience and robustness and provides structured approach for the investigation of both robustness and resilience. They divide the ATM system in two different dimensions: on the one hand, the stakeholders with the according systems and tools, on the other hand the physical movements of aircraft. The motion of the aircraft not only depends on the decisions made at the first level, but also on its performance characteristics. As a qualitative measure of resilience, propose the comparison of the time of deviation T_d – defined as the time between the beginning of the disruption and the time in which the performance reaches the lowest level - with time of recovery T_r - defined as the time to return to the unperturbed state. Then, it is possible to distinguish among:

- High resilience, if the time of deviation is considerably longer than the time of recovery;
- Medium resilience, if the time of recovery and deviation are comparable;
- Low resilience, if the time of deviation is particularly longer than the time of recovery.

(Cook et al., 2015; Cook et al., 2016), as part of the "ComplexityCost" projects, define mechanisms to afford resilience for one or more stakeholders during disturbance. To each mechanism, a monetary cost is assigned. The authors propose a cost resilience metric as a function of the tactical costs associated with each investment mechanism and the cost associated with a disrupted flight or passenger in presence and absence of a mechanism.

In (Stroeve et al., 2013; Stroeve et al., 2011; Stroeve & Everdij, 2017), an agent-based approach is proposed to support a more systematic analysis of resilience in ATM. They use agent-based modelling and simulation to analyse the capability of the ATM system to deal with disturbances and performance variability. The model includes a set of model constructs, which represent key aspects of evolution of agents' states and interactions. Their approach can represent a wide variety of performance variability in complex ATM scenarios and has the potential to systematically analyse risk and resilience.

(Palumbo & Filippone, 2017) propose a novel methodology and approach for resilience engineering in ATM; the paper summarizes the results accomplished in a SESAR Long Term Research project, SAFECORAM (Filippone et al., 2016; Palumbo et al., 2015). Their approach attempts to develop an ATM performance measure which incorporates the 11 key performance areas defined by ICAO, and resilience is defined as the level of residual ATM global performance. However, their approach necessitates a number of quantitative models that have not been defined yet, thus their model is still far from being defined.

3.3. Summary

Transportation systems are often subject to disruptions, such as technical failures or large-scale natural disasters, which are becoming more frequent and impactful. Since the efficient functioning of transportation systems is vital for the safety and well-being of societies in developed and developing countries, in recent years much research efforts were devoted to identifying and minimizing the impacts caused by disruptions – such as technical failures or natural disasters - on transportation systems. The literature related to resilience in the context of transport area has grown particularly, even if definitely more attention has been paid to vulnerability rather than resilience. A plethora of studies have been conducted focusing on different transportation modes, such as roadways, public, freight, maritime, railway transportation systems. Most of these studies evaluate resilience by considering one or both of the following aspects: system performance under disrupted conditions, and the speed and resources required for recovery to original functional states. However, also in the transportation sector, measures to determine comprehensively resilience in its multiple aspects are still missing.

Despite the large amount of works published in various domains regarding the concept of resilience, and in particular regarding the transportation field, the number of studies related to air transportation is quite limited in number. A comprehensive review of past studies regarding air transport resilience shows that, in literature, resilience can be evaluated at three different levels: network, airlines and airports. Most of the research efforts concentrates on determining the resilience of air transport network as a whole; besides, handful of works focus on the operations of individual carriers, or of alliances of airlines. Whilst, only few studies estimate the resilience at the individual airport level.

Among these studies, the majority evaluate air transport resilience by adopting a topological-based approach. The analysis of air transport network resilience by using a strictly topological approach is very efficient, however such studies neglect a large number of factors, most importantly the dynamic interaction between supply and demand and their inherent stochastic processes are not captured in these models. On the other side, system-based approaches, despite being more computationally expensive, describe more in detail the structure of the real system and delays' dynamic propagation.

This thesis aims at contributing to the resilience research at the airport level, which is the least studied but not the least important. In fact, airport nodes constitute a crucial element in the air transport network where the majority of delays occur, often creating bottlenecks for the entire system. It is unlikely to determine disruptions impacts on the air transport network as a whole, if they are not completely understood at the airport level. In line with previous literature, a system-based approach is adopted, which allows to model system dynamics and interactions among different components of the airport system. However, while previous resilience studies at the node level mainly perform post-disruption impacts assessments, here a flexible framework is provided to determine resilience and vulnerability of a generic airport system in the wake of a generic disruption.

Table 3.1. Taxonomy of reviewed papers

Authors, year	Year	Vulnerability / Robustness	Resilience	Conceptual	Network	Airline	Airport	ATM	Topological	System-based	Resilience capacity/aspect	Indicator
Kim and Yoon	2020	●			●				●		Absorptive	Number of operable flights and size of the largest connected component
Cerqueti et al.	2019		●		●						Absorptive	Ability to avoid shock propagation
Janic	2019		●			●				●	Absorptive	Percentage of performance loss, by considering five different indicators of performance
Reichardt et al.	2018 2019		●	●	●						Anticipation	-
Thompson and Tran	2018 2019		●								Absorptive Restorative	Number of potentially impacted passengers
Chandramouleeswaran and Tran	2018		●		●					●	Absorptive	Mahalobis distance
Clark	2018		●		●				●		Absorptive Restorative	Size of the giant component
Damgacioglu et al.	2018		●				●			●	Absorptive Restorative	Taxi in and taxi out times
Klophaus and Lordan	2018	●				●			●		Absorptive	Normalized average edge betweenness
Malandri et al.	2017		●				●			●	Absorptive Restorative	Recovery time and generalized travel cost
Roy et al.	2017	●			●				●		Absorptive	
Soria et al.	2017	●			●				●		Absorptive	Size of the giant component
Stroeve et al.	2017 2013 2011		●					●		●	-	Human performance variability
Palumbo and Filippone	2017		●					●		●	Absorptive	ICAO Key Performance Indicators

Table 3.1. (continued) Taxonomy of reviewed papers

Authors, year	**Year**	**Vulnerability / Robustness**	**Resilience**	**Conceptual**	**Network**	**Airline**	**Airport**	**ATM**	**Topological**	**System-based**	**Resilience capacity/aspect**	**Indicator**
Sun and Wandelt	2017	●				●			●		Absorptive	Size of the giant component
Sun et al.	2017	●			●				●		Absorptive	Giant component, unaffected passengers with rerouting, survived links
Voltes-Dorta et al.	2017		●				●			●	Absorptive Restorative	Average delays and passengers' relocation rates
Voltes-Dorta et al.	2017b	●			●					●	Absorptive Restorative	Aggregate delays
Asgary et al.	2016	●				●				●	Absorptive	Disrupted flights
Cook et al.	2016		●					●		●	Anticipation Absorptive Restorative	Costs of recovery mechanisms
Dunn and Wilkinson	2016		●		●				●		Response	proportion of cancelled air routes and closed airports
Li et al.	2016	●			●				●		Absorptive	Hazard covered area and impacted nodes
Filippone et al.	2016		●					●		●	Absorptive	ICAO Key Performance Indicators
Lordan et al.	2016	●				●			●		Absorptive	Size of the giant component
Marzuoli et al.	2016		●				●			●	Restorative	Arrival delay
Marzuoli et al. (b)	2016		●				●			●	Absorptive	Delayed, diverted and cancelled flights
Yoo and Yeo	2016		●		●				●		Adaptive	Number of required nodes to replace the flow of the removed node
Agrawal et al.	2015	●			●				●		Absorptive	Size of the largest connected component

Table 3.1. (continued) Taxonomy of reviewed papers

Authors, year	**Year**	**Vulnerability / Robustness**	**Resilience**	**Conceptual**	**Network**	**Airline**	**Airport**	**ATM**	**Topological**	**System-based**	**Resilience capacity/aspect**	**Indicator**
Cook et al.	2015		●					●			Anticipation Absorptive Restorative	Costs of recovery mechanisms
Janic	2015		●		●					●	Absorptive	Friability and costs
Lordan et al.	2015	●				●			●		Absorptive Adaptive	Normalized average edge betweenness and network efficiency
Palumbo et al.	2015		●					●		●	Absorptive	ICAO Key Performance Indicators
Lordan et al.	2014	●			●				●		Absorptive	Size of the giant component
Li et al.	2014	●			●				●		Absorptive	Clustering coefficient, diameter and efficiency
Cardillo et al.	2013		●		●				●		Adaptive	Possibility of re-scheduling passengers
Glushenko and Foerster	2013		●	●				●		●	Restorative	Recovery time relative to the duration of the disruption
Hossain et al.	2013		●		●				●		Absorptive	inverse geodetic length and nodes connectivity
Yan et al.	2013	●			●				●		Absorptive	Average edge betweenness
Wilkinson et al.	2012	●			●				●		Absorptive	Proportion of cancelled routes relative to the proportion of closed airspace
O'Regan	2011		●	●	●						-	-
Wuellner et al.	2010		●			●			●		Absorptive	Size of the largest connected component; global travel cost
Pejovic et al.	2009	●					●			●	Absorptive	Delayed, cancelled, diverted flights, emissions, costs of delays

4. AIRPORT DISRUPTIONS

4.1. Introduction

In the last decade, the proper functioning of airport operations all over the world have been often compromised by unexpected and severe disruptive events, such as extreme bad weather, natural disasters of failures of airport's components. Such events are called "disruptions" and can vary in size, cause and impact (www.eurocontrol.int), often constituting a risk for peoples' injuries and lives. Recent disruptions showed that the air transport system is extremely vulnerable to such kinds of events.

For example, in January 2014, four weeks of extremely adverse weather affected the performance of U.S. North-Eastern airports: heavy snow, record-breaking cold temperature and two polar vortexes provoked a number of delays and cancellations. More than 300,000 flights were delayed and approximately 49,000 flights were cancelled, affecting 30 million of passengers. The delays and cancellations were estimated to cost between \$75 and \$150 million to industry, \$2.5 billion to passengers (Clark et al., 2018).

Generally, causes of disruptions may be internal or external to the airport system. In the latter case, disruptive events include failures of the airport's infrastructure, such as runway's or taxiway's pavement, industrial actions of the airport staff, incidents/accidents or technical failures of airport's components - for example radar or ground vehicles. External disruptive events are usually extreme bad weather, such as heavy snowfalls (such as the example above-mentioned), strong winds, hurricanes, tornadoes, thunderstorms with flooding. Additional disruptive events include man-made disruptions, such as terroristic attacks and threats, and natural disasters, which includes volcanic eruptions, tsunamis and earthquakes, for example the Great East Japan Earthquake (Janić, 2018; Trucco et al., 2014).

The above-mentioned disruptive events generally occur unpredictably and randomly, both in space and time. Sometimes, different disruptions may occur simultaneously, and therefore their impacts may be interrelated. Minor events are dealt with throughout standard operational procedures. However, major disruptions such as man-made disasters - physical or cyber-attacks systems failure - or natural disasters - volcanic eruptions, severe adverse weather - might seriously jeopardize normal network operations.

The aforementioned disruptive events usually cause significant and unexpected loss of airport's capacity, implying that its current operations generally substantively deviate from the scheduled ones. Such deteriorations generally produce important delays, cancellations and rerouting of the affected aircraft.

Depending on the type of the event, the deteriorating planned performances may last from few hours to longer period of time – several hours or days.

Because of the strong connection between incoming and outgoing flights, even if only one airport is directly affected, consequences may spread and undermine the regularity of operations at other airports. If flights depart late from the affected airport, arrival delays usually manifest at the at the unaffected airport; these delays, if not adequately reduced by spare buffer times, usually lead to departure delays. Certain disruptions are so serious that knock-on effects might affect flight operations in an entire region or country.

Moreover, the deteriorated airport operational performance inevitably results in economic losses and social impacts at different levels, experienced by the stakeholders involved: airport operators, airlines and passengers (Janić, 2015). Airlines usually incur in profit losses caused by the cancelled or re-routed flights and, generally, this result in aircraft and crew being out of position with respect to scheduled itineraries. Moreover, they may be imposed the additional cost of providing alternative transportation, food and beverage and, depending on the amount of delay, money refund to compensate passengers' inconvenience (Shavell, 2001). Passengers, which are usually the most affected stakeholders, are imposed direct cost of the lost time caused by the long delays or cancellations. They arrivals are delayed, and scheduled connections may be missed, thus provoking discontent and probably leading to a future boycott of the airline.

In addition, impacts are especially magnified at hubs, which are generally congested airports and whose effective functioning depends on the ability of passengers are able to make scheduled connections. Moreover, whereas disruptions occur during peak hours, the effects are particularly dramatic.

4.2. Airport disruptions in Europe from 2015 to 2019

During the last years, in Europe, several unplanned disruptions imposed capacity reductions at certain airports, causing serious delays and schedule inefficiencies. In 2018, "*a record number of adverse weather events and industrial actions severely disrupted network operation*" (EUROCONTROL, 2018). Also in 2019, disruption has seriously affected European airports' operations. Up to September 2019, the average airport delay reached 22,725 minutes per day, with an increase of 5% with respect to the previous year. The main causes of airport disruptions have been capacity related. As shown in the figure 4.1. below, the airport which has been the most affected is Amsterdam Schiphol, followed by Athens.

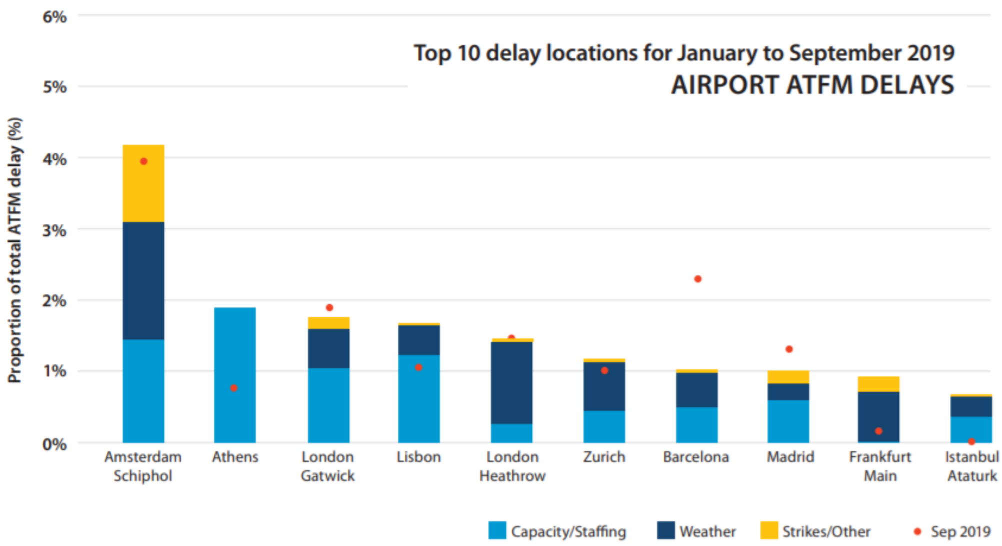


Figure 4.1. Top 10 delayed European airports in 2019 (January-September). Source: *https://www.eurocontrol.int/our-data*

In this section, statistics are reported regarding the types of disruptions that affected European airports during the last years, from 2015 to 2019. A disruption is defined as an unplanned disruptive event which affects airport operations provoking more than 1,000 minutes of ATFM (Air Traffic Flow Management) delay. Data are retrieved from EUROCONTROL's publications, in particular from the "Annual Network Operations Report", which is published every year (EUROCONTROL, 2015, 2016, 2017, 2018). From a few years, EUROCONTROL collects data regarding airport disruptions, specifying the date of the disruptive event and the airport affected and the total ATFM delay caused. However, information related to events before 2015 is quite sporadic and many data are missing. For this reason, in the following, we will consider only disruptions successive to January 2015. The data collected include a total number of 147 disruptions.

The map in figure 4.2 displays the number of disruption occurrences in the period 2015-2018 at European airports. Each airport affected is represented by a circle, whose radius is proportional to the number of occurrences. The colour scale is indicative of the airport's number of movements per year: the darker the colour, the higher the number of movements.

The most affected airport during the period of analysis is Amsterdam Schiphol followed by Lisbon airport, London Gatwick, Paris Charles de Gaulle and Paris Le Bourget. Generally, the airports which experienced the highest number of disruptions are the ones with the highest number of movements per year. However, there is not a definite relation between the size of the airport and the number of disruptions. In fact, the number of disruptions is strongly influenced also by external factors, such as environmental ones. For example, Catania-Fontanarossa Airport has been frequently disrupted because of the vicinity to the active volcano Etna.

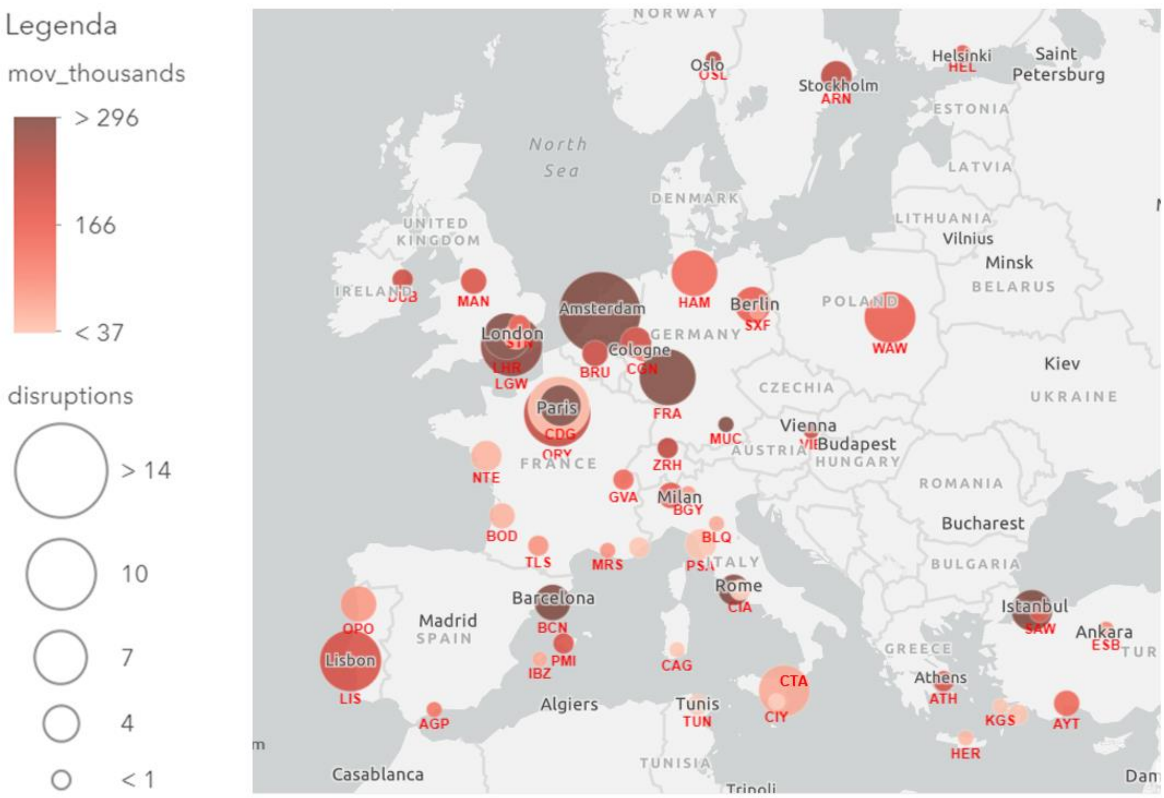


Figure 4.2. European airports' disruptions between 2015 and 2018

Six main groups of disruptions' causes were identified: technical or infrastructural issues, extreme weather, incidents, industrial actions, security issues (evacuations/terroristic attacks). Moreover, other types of disruptions have occurred, including events such as festivals and military celebrations. Each of these groups includes several disruption types, which shown in Table 4.1.

Table 4.1. European airports' causes and types of disruptions (2015 - 2018)

Disruption cause	Disruption type
Others	Events
Extreme weather	Snow
	Thunderstorm
	Volcanic eruption
Incident	Aircraft incident
	Aircraft on runway
	Aircraft diversion
	Drone incident
	Emergency landing
	Runway contamination
	Security incident
Industrial action	ATC Industrial action
	Ground personnel industrial action
Infrastructural problem	Runway maintenance/closure
	Taxiway and/or apron improvements
Security related	Dangerous objects
	Evacuation
	Fire
	Military activity
	Terrorism
Technical problem	ATC system/communication issues
	Ground operations issues
	ILS issues
	Lighting issues
	Power issue
	Radar issues
	VOR issues

The main causes of disruptions were technical problems (46%), followed by infrastructural problems (18%), industrial actions (11%) and security-related issues (See Figure 4.3). Less frequent have been extreme weather (2%), incidents (8%) and sporadic events (5%). The low percentage of extreme-weather related causes may seem strange, as weather is established to be the main cause of airport delays, as mentioned at the beginning on this Section 4.2; however, here only disruptions which caused more than 1,000 minutes of ATFM delays are considered and, evidently, adverse weather usually do no cause that much delay at the same time. As shown in the graph in figure 4.4, among the disruptions caused by technical failures, the majority of problems is caused by radar issues (30%) and communication problems (22%). Other technical problems include power outages, lighting/ILS/VOR malfunctioning, or failures of ground operations equipment.

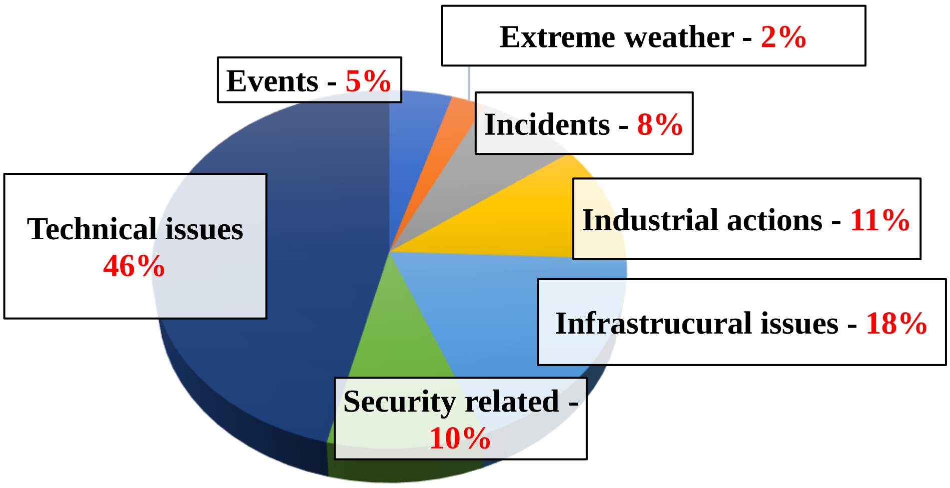


Figure 4.3. Causes of disruptions at European airports (2015-2018)

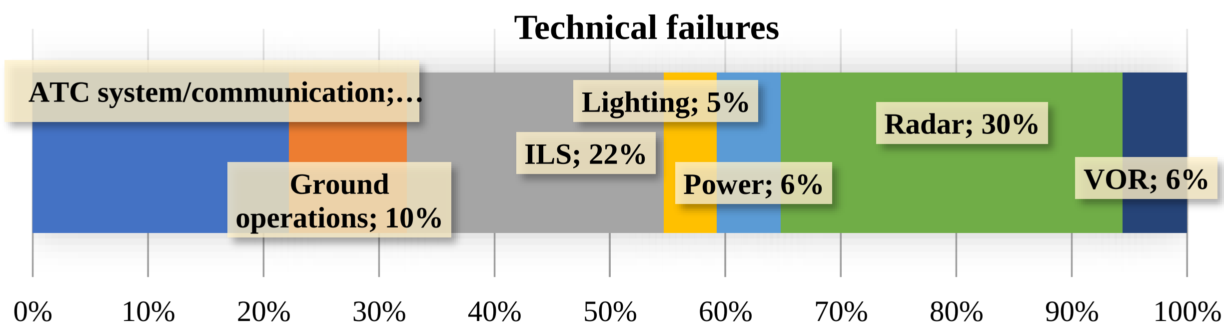


Figure 4.4. Types of disruptions caused by technical problems at European airports (2015-2019)

Each disruption undermines airport operations in a different way. The disruptions were clustered in 4 groups depending on which airport operation is directly affected, i.e.:

A. Reduced landing or take-off capacity (e.g. radar problems):
B. Reduced runway capacity (e.g. broken aircraft on runway);
C. Reduced ground operations capacity (e.g. staff strikes);
D. Temporary closure of the airport (e.g. fires/volcanic eruptions).

In the first cluster (figure 4.5a) are included all those disruptions which cause a reduction in the approaching and landing capacity, as well as take-off and climbing capacity. Delays are thus provoked by unavailability of the slots necessary to land or take-off. This is the case for example of radar problems and issues with the instrumental landing system, as well as thunderstorms. Cluster B (figure 4.5b) includes disruptions related to the availability of runways and taxiways. For example, if the runway is not available because of an incident, or because of holes on the runway or taxiway. In these cases, the runway/taxiway cannot be used and, thus, aircraft are re-routed to alternative ones, causing congestion and delays. Cluster C (figure 4.5c) refers to disruptions affecting ground operations, for example ground operators' industrial actions or technical failures of ground equipment. The last cluster (figure 4.5d) refer to disruptions causing the complete closure of the entire airport for a certain time. This is the case of evacuations due to security alert or fires, or the case of power failure. Table 4.2. indicates types of disruptions included in each cluster.

Table 4.2. Disruption type per cluster

A	B
ATC Industrial action	Aircraft incident
ATC system/communication issues	Aircraft on runway
Diversion	Drone incident
Emergency landing	Runway contamination
Events	Runway maintenance/closure
ILS issues	Security incident
Lighting issues	Taxiway and/or apron improvements
Radar issues	
Snow	
Thunderstorm	
VOR issues	

C	**D**
Ground operations issues	Dangerous objects
Ground personnel industrial action	Evacuation
Thunderstorm	Fire
	Military activity
	Power issue
	Terrorism
	Volcanic eruption

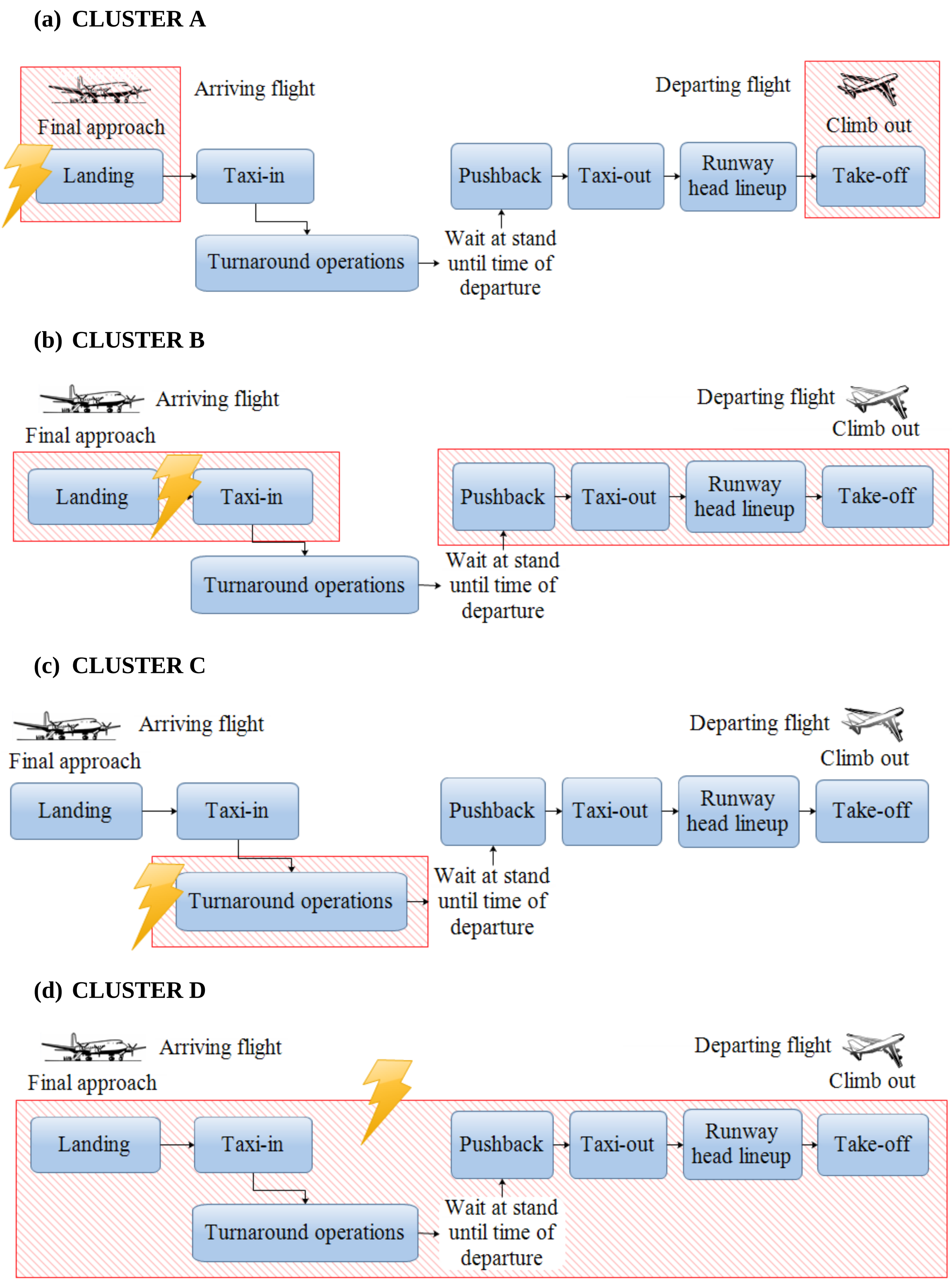


Figure 4.5. Disruptions' clusters

Figures 4.6a and 4.6b show the causes of disruption for each cluster. The majority of problems affecting airports' landing or take-off capacity are technical-related, in particular radar failures. Cluster B is composed of infrastructural problems and incidents. In the third cluster, a half of the disruptions is caused by industrial actions, a half from technical problems. The last cluster includes principally security-related disruptions, such as evacuations or fires.

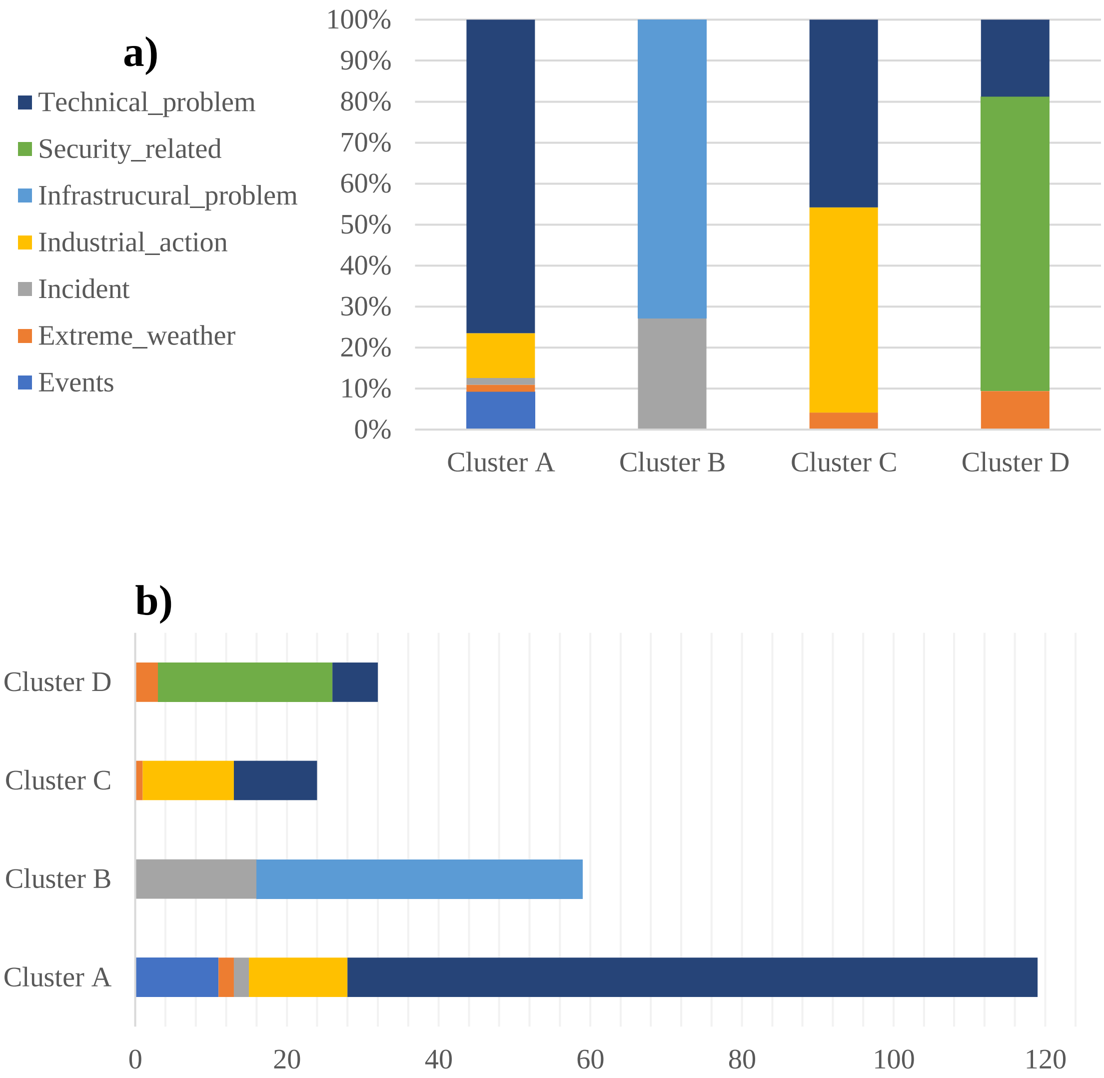


Figure 4.6. Disruption cause per cluster, in percentage (a) and absolute value (b)

4.3. Costs of disruptions

As specified in Section 4.1, airport disruptions result in important delays, cancellations and rerouting of the affected aircraft, provoking important economic losses for service providers and passengers. EUROCONTROL, in a detailed report, provides estimates of the cost of delays, cancellations and diversions in Europe (EUROCONTROL, 2018).

The cancellation cost is defined by EUROCONTROL (EUROCONTROL, 2018) as the average cost of cancelling a commercial scheduled flight on the day of operation. According to EUROCONTROL, the main causes of cancellations are industrial actions, political reasons (e.g. conflicts), natural disasters and technical failures. EUROCONTROL estimates the system-wide average flight cancellation cost $COST_c$ to be:

$$COST_C = 17{,}650\ € \qquad \text{(Eq. 4.1)}$$

The value refers to cancellation on the day of operation and includes:

- Loss of revenues;
- Crew and catering costs;
- Passenger compensation for denied boarding and missed connection (estimated on the application of the EU261/2004 regulation);
- Luggage delivery costs.
- Service recovery costs, including food and beverage, accommodation, passenger vouchers and telephone calls;
- Loss of future value, i.e. passenger opportunity costs;
- Operational savings (fuel, airport and navigation fees, maintenance, handling outstations, lounges outstations).

Cost of diversion indicates the average cost of the diversion of a flight to an airport other than the one initially planned. EUROCONTROL estimated the cost of a diverted flight $COST_d$ to be:

$$COST_d = 7{,}400\ € \qquad \text{(Eq. 4.2)}$$

As for the cost of delay, recently, much effort has been dedicated to the attempt to quantify the cost of one minute of delay (Cook et al., 2016; Cook et al., 2009; Cook et al., 2004).

EUROCONTROL provides the estimates of the average cost per minute of ground or airborne delay of a commercial passenger flight. EUROCONTROL estimates the network average cost of one minute of ATFM delay cost to be:

$$cost_r = 100\ €/min \qquad \text{(Eq. 4.3)}$$

Then, the average cost $COST_r$ of a delayed flight is given by:

$$COST_r = costr * DEL = 100 * DEL\ \ € \qquad \text{(Eq. 4.4)}$$

Where *DEL* is the delay experienced by the flight.

The estimate is based on a study undertaken by the University of Westminster, in which a detailed assessment of the delay costs for 15 specific aircraft types and the average delay cost per minute in Europe are estimated (Cook & Tanner, 2015). The report is considered to be the reference document for European delays direct costs, both at the strategic and tactical stages. Cost assumptions include direct costs (fuel, crew, maintenance, etc.), the network effect (i.e. cost of reactionary delays) and airline related passenger costs (rebooking, compensation, etc.). Costs related to the EU emission trading scheme are not included.

5. METHODOLOGY

5.1. Overview

After having described in previous Chapters the context of the scientific literature on resilience in air transportation, in which the present work is settled, and which is the aim of the present work, and the factors which lead to the development of this work, in this Chapter it is presented in detail the methodology used to perform the resilience analysis of airport operations and to reach the goals established.

The main objective of this project is to provide a framework that allows to evaluate performance losses and consequences due to unexpected disruptions affecting airport operations, supporting the development of a methodology for estimating vulnerability and resilience indicators for airport operations. Towards this aim, the methodology adopted includes three phases.

In the first phase, resilience and vulnerability indicators are defined and evaluated for a target airport affected by a certain type of disruption.

To estimate the effects generated at a target airport by a disruption, a general approach is to describe both the reference – i.e. in the absence of disruptions - and disrupted scenarios and assess the difference in selected system performance indicators (see Section 2.3). This approach is adopted also here, and towards this aim, the first phase includes five main steps, summarized in figure 5.1.

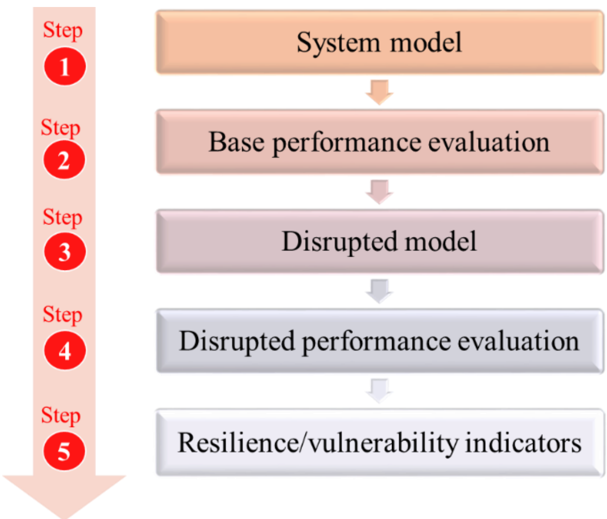


Figure 5.1. General five-steps methodology

In the first step, the operations at a generic airport *A* are modelled in a nominal situation, i.e. without disruptions, referred to as "baseline scenario". The model includes all main processes which take place in the airport airside area, from the flights' approaching to the take-off. All main factors are included in the analysis in order to make the model as realistic as possible, including inherent uncertainties in the system.

The developed airside model consists of two hierarchical sub-systems. The first one describes the LTO (Landing and Take-Off) cycle from landing to take-off. Here, are taken into considerations all the features of the airport which influence the operations the most, such as the number of runways, of aircraft parking stands. The second system focuses on modelling aircraft turnaround operations, starting from the moment the aircraft reaches the parking position after landing. The model includes all relevant activities as a function of ground handling operator's availability. The model allows to take into consideration the dynamics of the airport system, in which airport are strictly connected and resources are limited. These two models will be described respectively in sections 5.2 and 5.3.

In the second step, the performance in the reference scenario - referred to as "base performance" - is evaluated in terms a set of indicators which reflect the correct functioning of airside operations. The performance indicators measured, described in Section 5.4, are the average service rate, the total delay, and the average turnaround time.

Once the baseline scenario has been modelled for the given airport, alternative scenarios can be explored, such as disrupted ones. However, every disruption is unique in itself and has different consequences on the airport system. In the third step, the disruption of interest is chosen and modelled based on the clustering presented in Chapter 4. The disruption causes a degradation of the system's performance, as described in Section 5.5.

In the fourth step (Section 5.6), the performance in the disruption scenario is assessed. Because of the dynamicity of the airport system, disruptions cause cascading failures on airport operations which; in the model presented in this works, such knock-on effects are taken into consideration. The base performance indicators are chosen as a basis for the analysis and the variation between the new state and the baseline state is measured. Such gradient will reflect the impact of the specific type of disruption on the target airport system.

The fifth and last step of the analysis comprises the evaluation of vulnerability and resilience indicators. The vulnerability indicator should reflect the magnitude of the deviation of the aforementioned indicators from the targeted system performance level. In the present work, vulnerability is evaluated int terms of equivalent flight cancellations during the period of disruption. Besides, the resilience indicator should also include system's ability to recover in the most efficient ways. Here, resilience is defined as "*the airport's ability, during and immediately after the occurrence of a disruptive event, to reduce efficiently both the magnitude and duration of the deviation from targeted operational performance levels*". Based on this definition, resilience is evaluated as a function of the loss of throughput capacity and of the total duration of the disruption. The indicators proposed will be described in Section 5.7.

In the second phase (*implementation phase*), the model developed is implemented by using a generic simulation software, AnyLogic. Given the complexity and stochasticity of the operations modelled, simulation was found to be the most proper tool to evaluate airport's performance.

Once implemented the model, it is applied to four different disrupted scenarios, one for each of the clusters identified in Chapter 4. Both the disrupted and baseline scenarios are validated by comparing simulations' output with real data. When the model is validated, it can be used to explore different scenarios. In this thesis, the simulation model is used to analyse the disruptions which affected European Airports between 2015 and 2018 (and described in Chapter 4).

As third and last phase of the methodology, results obtained from the simulations have been used to build a Bayesian Network (BN). BNs are graphical model that represent the probabilistic dependence between variables. In this work, the BN is built by considering variables related to airport and disruption characteristics. The BN will allow to predict and assess resilience and vulnerability indicators as a function of a large number of variables.

The diagram in figure 5.2 shows the main steps included in the methodology adopted in this work. The remaining of this Chapter will be devoted to describing the first phase of the methodology, referred to in grey in Figure 5.2. The implementation phase (represented in green in the same figure) will be illustrated in Chapter 6 and results will be shown in Chapter 7. The last phase, indicated in orange in the figure below, will be detailed in Chapter 8.

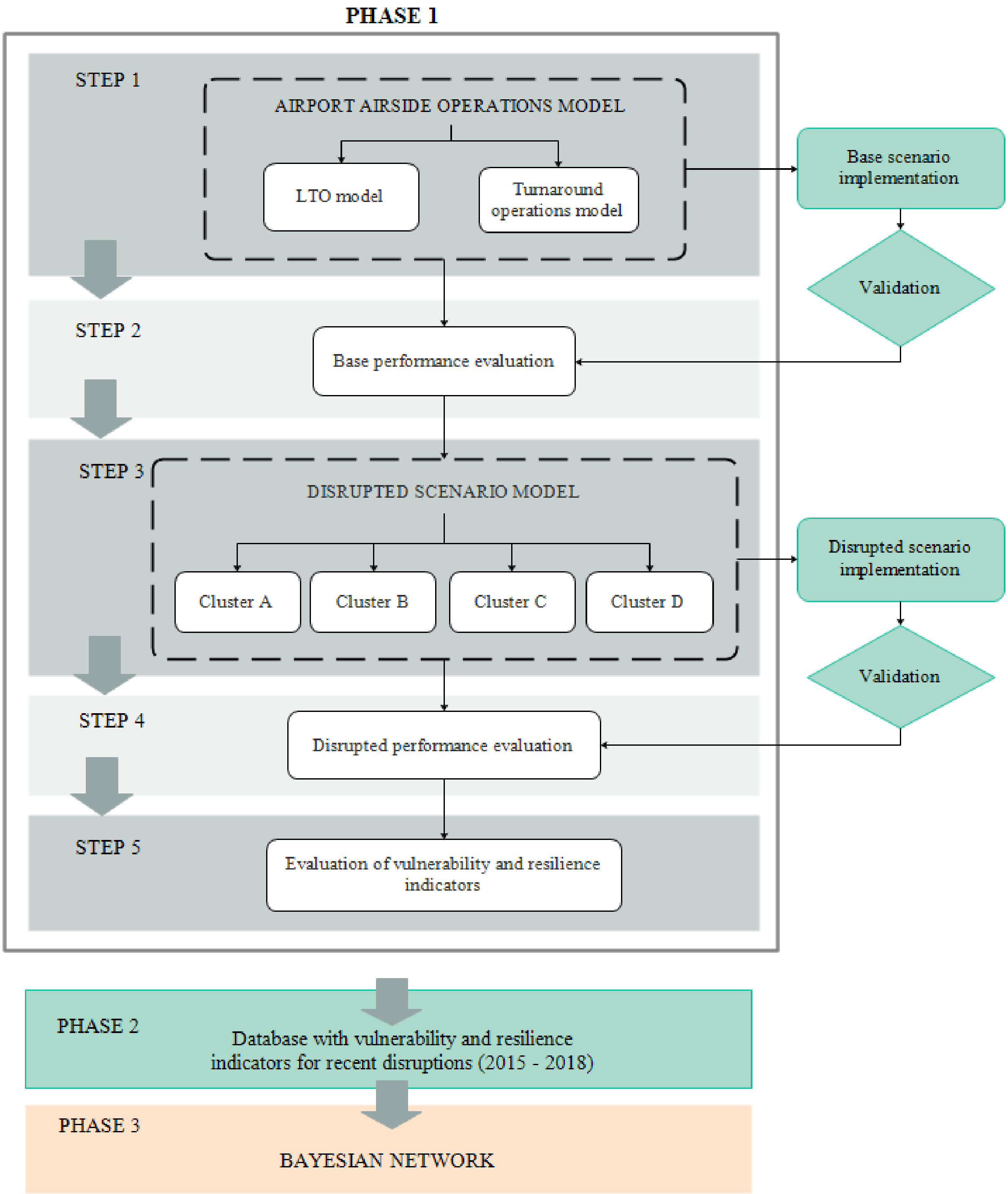


Figure 5.2. Methodological approach

5.2. Airside operations modelling

5.2.1. Logic flow of the model

This section describes the main methodological steps undertaken to model airside airport operations in the current scenario, i.e. in the absence of disruptions. The scenario model includes all relevant dimension of the system that may influence the performance in face of a disruption.

The developed airside model consists of two hierarchical sub-systems: the first layer (higher level) describes the landing and take-off cycles (LTO); in the second one (lower level) aircraft turnaround operations are modelled including all main activities as a function of ground handler's operators' availability. A discrete event approach is adopted to build the model, as both the LTO cycle and aircraft ground handling operations can be viewed as an ordinate sequence of steps that each aircraft must undergo at the airport. The model, adapted from (Khammash et al., 2017), consists of five main steps: landing, taxi-in, turnaround, taxi-out and take-off. The second one (lower level) focuses on turnaround operations and all main activities are modelled as a function of ground handling operators' availability. A turnaround model exists for each ground handler.

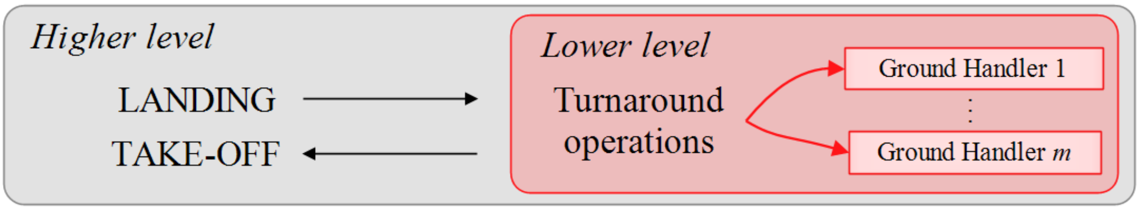


Figure 5.3. Logic of the model

At the higher level, the organization of the LTO operations copes with the urgency to both provide safe landing in both presence and absence of disruptions aircraft and speed up take-off for scheduled aircraft, in order to keep safety and efficiency at the airport and reduce delays as much as possible. At the lower level, turnaround operations should be organized in order to comply with LTO exigencies while re-scheduling aprons occupancy and handling operations under limited resource constraints. A discrete event approach is adopted to model LTO cycle and turnaround operations, which are both an ordinate sequence of steps that each aircraft must undergo at the airport (Postorino et al., 2019).

5.2.2. LTO cycle model

Let *A(R,S,M,CAP)* be a generic airport composed of a number *R* of available runways and a number *S* of available aircraft parking stands. Airport *A* is operated by a number *M* of ground handlers.

Airport *A(R,S,M,CAP)* has a maximum landing and take-off hourly capacity CAP_A (movements/h), which depends on the runway system, the structure of the traffic, on the composition of airport's infrastructure and may be limited because of environmental constraints, such noise pollution. Airport capacity refers to the ability of an airport to handle a given volume of traffic (EUROCONTROL, 2016). There are two commonly used definitions of airside hourly capacity:

- *Technical capacity*: indicates the maximum number of movements that can be performed with a given infrastructure in one hour, thus complying with the separation requirements;
- *Declared capacity*: indicates the maximum number of movements that can be accommodated by the airport in one hour, taking all elements of the operations chain into account (runway systems, terminal airspace, taxiways, environmental constraints). This value is usually 80-90% of the technical capacity (Senguttuvan, 2006).

In this work, we assume that airport capacity CAP_A is equal to the technical capacity, thus equal to:

$$CAP_A = CAP_{A,DECLARED} * \alpha \; [\frac{movements}{hour}] \qquad \text{(Eq. 5.1)}$$

Where $CAP_{A,\,DECLARED}$ is the declared capacity of airport *A(R,S,M,CAP)* and $\alpha > 1$.

Let K_A be the set of aircraft due to land at airport *A(R,S,M,CAP)* in the period of analysis *T*. Each arriving aircraft $k_A\,(a,m,w)$ is operated by airline *a*, serviced by ground handler *m* and is of a specific type *w*, i.e. narrow or wide body. Arrivals and departures occur in the order of the flight schedule. The model starts at the beginning of the approaching phase. Aircraft $k_A\,(a,m,w) \in K_A$ approach the terminal manoeuvring area of the airport at time ta_k:

$$ta_k = STA_k - t_{approach} \qquad \text{(Eq. 5.2)}$$

where STA_k is the Scheduled Time of Arrival (*STA*) of aircraft $k_A\,(a,m,w)$ and $t_{approach}$ is the time required for the approaching phase. At the end of the approaching phase, the aircraft is assigned to one of the runways $r \in R$ of airport *A(R,S,M,CAP)*. If runway *r* is free, aircraft $k_A\,(a,m,w)$

starts landing. If there are other aircraft waiting for landing, $k_A\,(a,m,w)$ queues following a FIFO scheme. Aircraft $k_A\,(a,m,w)$ lands with a constant deceleration given by:

$$d_k = \frac{1}{2}\frac{(v_l - v_r)(v_l - v_r)}{x_r} \qquad \text{(Eq. 5.3)}$$

Where x_r is the length of the runway, v_l is the speed at the beginning of the landing phase and v_r is the aircraft speed at the end of the landing process, i.e. the aircraft speed on taxiways.

After landing, the following sequential steps occurs:

- *Taxi-in:* the aircraft leaves the runway and, following taxiways, moves towards its assigned stand *s* by using the shortest path. Stand allocation is not dynamic and it depends on a series of parameters and variables, including aircraft type and airline. If stand *s* is occupied, the aircraft moves toward the nearest free stand. The duration of the taxi-in phase is a function of the aircraft speed v_{taxiin} and of the distance between the runway *r* used for landing and the assigned stand *s*.
- *Turnaround operations:* Once the aircraft arrives at stand *s*, ground handling operations are performed by the corresponding ground handler *m*. Here, all necessary operations are performed to prepare the aircraft for the successive departure. Turnaround operations' duration depend on the duration of each single activity performed, as specified in the following Section 5.2.3, where the sub-model relative to turnaround operations. One sub-model exists for each ground handler *m*.
- *Pushback*: whether turnaround operations are completed, pushback operations start at STD_k, i.e. the Scheduled Time of Departure (*STD*) of aircraft $k_h\,(a,m,w)$. Pushback operations have a duration $t_{pushback}$ and include tractor connection, proper pushback and tractor disconnection.
- *Taxi-out and Runway head line-up*: after pushback, the aircraft is assigned a departing runway *r,* which may be the same used for landing or not. Then, taxi-out procedure is performed, and the aircraft arrives at the runway head, where it waits for runway clearance for a time t_{vortex}, which is the time needed between two consecutive runway utilizations to allow aircraft tail-vortices to dissolve. The duration of the time t_{vortex} depends on the type of the aircraft (narrow or wide body) of the previous runway utilization. The aircraft eventually queue if other aircraft is waiting for runway clearance. If the number of queuing

aircraft exceed a threshold number MAX_{queue}, the aircraft is held at the stand until the next take-off.

- *Take-off*: After the time t_{vortex}, the aircraft can start take-off. Additional waiting times at the runway head may be due to queue or 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 equal to:

$$ac_k = \frac{1}{2}\frac{v_t^2}{x_r} \qquad \text{(Eq. 5.4)}$$

Where x_r is the length of the runway and v_t is the speed at the end of the take-off phase.

The LTO steps modelled are shown in blue in the figure 5.4 below.

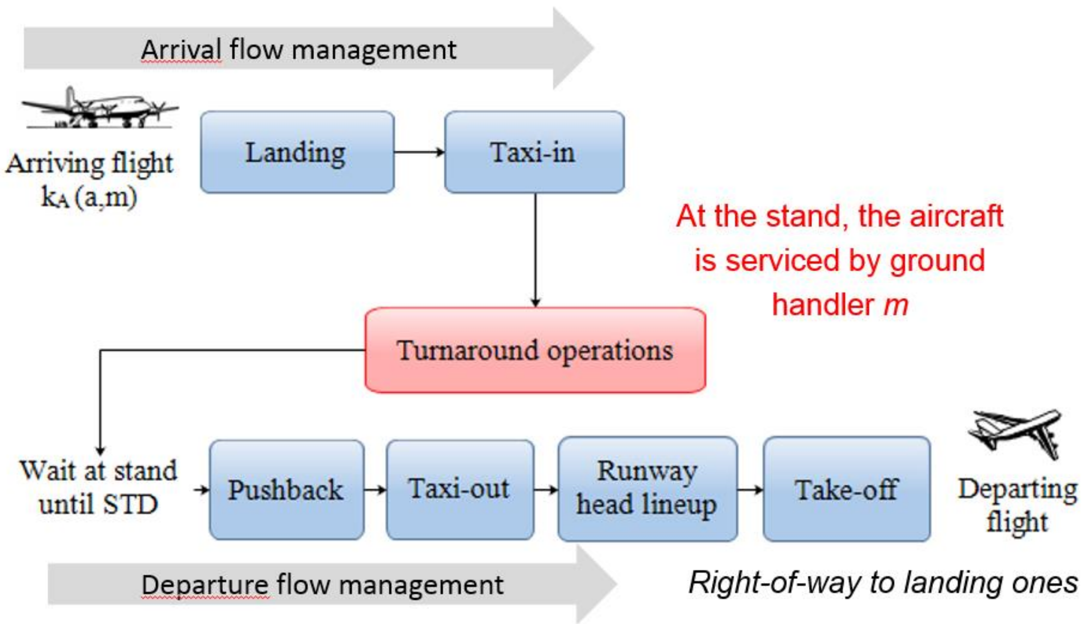


Figure 5.4. Airside operations modelled

Each aircraft undergoes the same sequence of events, from arrival to departure. Exceptions are made for *first departures* $k_{A,FIRST}$ *(a,m,w)* and the *last arrivals* $k_{A,LAST}$ *(a,m,w)*, which are modelled slightly differently.

Last arrivals $k_{A,LAST}$ *(a,m,w)* includes those aircraft which do not have other scheduled departures during the period of analysis *T*. These aircraft land in the same way of other aircraft, as described above. Once landed, they arrive at the assigned stand *s*, where turnaround operations are performed. However, at the end of turnaround operations, the aircraft do not have to proceed towards the runway, instead it reaches a remote stand position where it is parked until the end of the period of analysis *T*. The LTO model for last arrivals is shown in figure 5.5 (a).

On the other hand, *first departures* $k_{A,FIRST}(a,m,w)$ include those aircraft which are already at the airport at the beginning of the period of analysis *T*. These aircraft do not land at the airport during the period of analysis, therefore they only have to undergo the second part of the LTO cycle. After turnaround operations, pushback is performed, and the aircraft proceed towards its departing runway for take-off. First departure's LTO model is shown in figure 5.5. (b).

Also turnaround operations are slightly different for these aircraft. The different turnaround models for first and last departures will be described in the following Section 5.2.3.

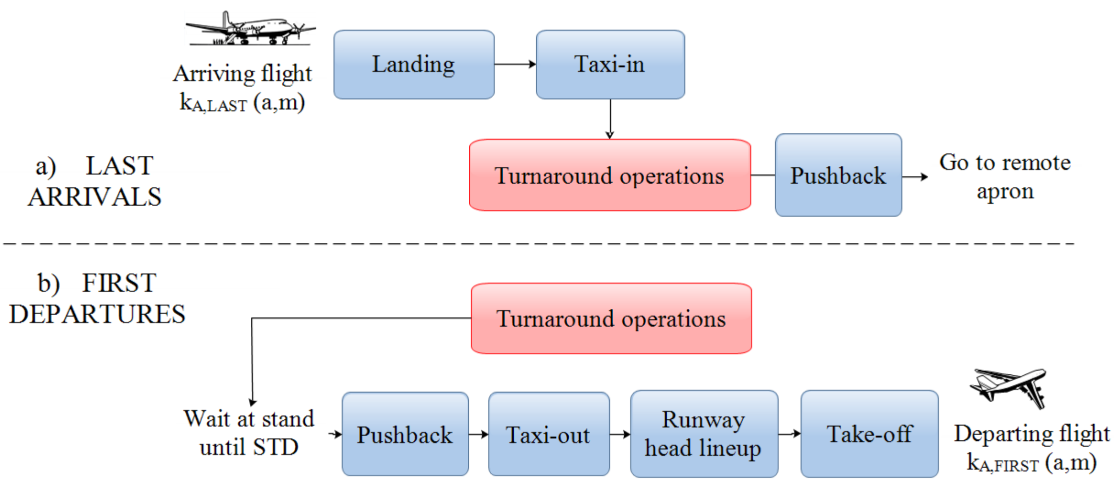


Figure 5.5. LTO model for (a) last arrivals and (b) first departures

5.2.3. Aircraft turnaround model

Aircraft turnaround is a fundamental component of airport operations and it includes all necessary activities for preparing an aircraft for the next departure.

The turnaround process begins at the so-called "on-bock time", when aircraft $k_A(a,m,w)$ reaches its parking position after landing and the chocks are placed in front of the aircraft wheels. Then, several activities *i* have to be performed, to handle the arriving aircraft and prepare if for the next departure. Because of regulations and physical restrictions, such as the limited amount of space around the aircraft, turnaround operations have to be performed in a precise chronological order. Some activities have to be performed sequentially, some other can be performed simultaneously (Schmidt, 2017). They are performed in a way to achieve maximum turnaround efficiency, which has been defined as the ability to execute the required operations within the available time in order to enable a punctual flight departure (Wu & Caves, 2004).

After chocks' positioning, passengers' stairs are positioned, or a boarding bridge is connected to the aircraft - depending on the stand position and the aircraft configuration - doors are opened. Then, passengers de-boarding starts together with baggage and cargo unloading. Concurrently, the potable water is replenished. According to hygienic standards, waste water servicing can begin only when potable water replenishment is finished (IATA, 2008). Refuelling activity usually begins after the completion of the disembarking process. As soon as the last passenger has de-boarded the aircraft, cleaning and catering activities are allowed to start and they are typically performed simultaneously. The cabin crew checks the aircraft's condition and equipment and prepares the aircraft for the successive flight. Trolleys are substituted by the catering provider and the cabin interior is cleaned. Once the cleaning, catering and refuelling operations are completed, the passengers of the following flight are boarded and, in the meantime, the cargo and baggage are loaded. Finally, when all these operations are completed, chocks are removed.

The activities modelled are shown in Figure 5.6. They must be performed in the order shown in the graph, where arrows express conditions necessary to perform the successive ones. If there is no arrow connecting two activities, they are independent of one another and therefore they can be performed simultaneously. Several service providers - ground handlers, fuel and catering suppliers - have to coordinate with each other in the best possible way to provide an efficient turnaround.

In the model, the following assumptions are made:

(1) refuelling takes place between disembarking and boarding, in the absence of passengers;
(2) the duration of certain activities depends on the aircraft type (narrow or wide body), since more time is needed to service bigger aircraft.
(3) no distinction is made regarding aircraft configuration (number of doors and hatches).

Each generic activity i is composed of a series of sub-operations o_i: for example, to allow passengers to disembark, stairs must be positioned near the aircraft and, at the end of the turn-around process, taken off. Each sub-operation o_i is completed in a time period t_{oi}, where t_{oi} is a stochastic variable with a known probability distribution. Table 5.1 shows all the operations and sub-operations included in the model, as well as the number of operators and resources required to perform them and the service provider responsible for the activity. When all these activities are completed, chocks are removed at the "chocks-off time" and pushback operations start.

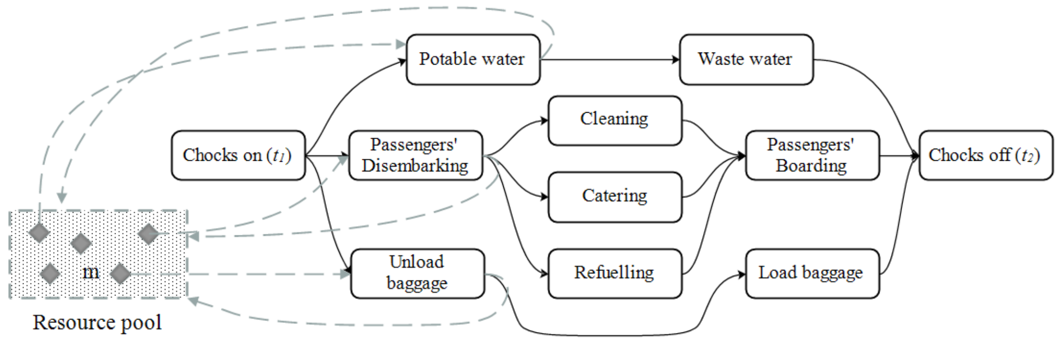


Figure 5.6. Turnaround model (Malandri et al., 2019)

Table 5.1. Turnaround operations and sub-operations modelled

i	Operation *i*	Sub-operation o_i	N° operators *j*	Resource	Owner
1	**Chocks on**	-	1	Chocks	Ground Handler
2	**Disembarking**	Stairs positioning	2	Stairs	Ground Handler
		Passengers disembarking	-		
3	**Cleaning**	Cleaning	2	-	Cabin Crew
4	**Catering**	Catering truck connection	2	Catering Trucks	Catering Company
		Departure catering loading			
		Arriving catering unloading			
		Catering truck disconnection			
5	**Potable Water**	Water truck connection	1	Water Truck	Ground Handler
		Potable water replenishment			
		Water truck disconnection			
6	**Waste Water**	Waste water truck connection	1	Waste Water Truck	Ground Handler
		Waste Water			
		Waste water truck disconnection			

7	**Baggage/Cargo Unloading**	Loader positioning	3	Bulk/Container loader	Ground Handler
		Arriving baggage/cargo unloading			
		Loader disconnection			
8	**Refuelling**	Fuel truck connection	1	Fuel Truck	Fuelling Provider
		Refuelling			
		Fuel truck disconnection			
9	**Baggage/Cargo Loading**	Loader positioning	3	Bulk/Container loader	Ground Handler
		Departing baggage/cargo loading			
		Loader disconnection			
10	**Passengers boarding**	Passengers boarding	-	Stairs	Ground Handler
		Stairs removing	2		
11	**Chocks off**	-	1	Chocks	Ground Handler

Additionally, for last arrivals and first departures, the turnaround model is slightly different.

In fact, last arrivals $k_{A,LAST}\,(a,m,w)$ do not have another scheduled departure during the period of analysis T. For this reason, they do not require to be prepared for the successive departure Thus in these cases, after chocks are placed, only a subset of the activities need to be performed, specifically: disembarking of passengers and unloading of baggage, potable and waste water, cleaning, catering and refuelling. Figure 5.7 (a) shows the turnaround model for last arrivals.

First departures $k_{A,FIRST}\,(a,m,w)$, on the other hand, only need to be prepared for the successive take-off. Thus, for these aircraft, the only activities to be performed are boarding of passengers and baggage loading. The turnaround model for first departures is shown in figure 5.7 (b).

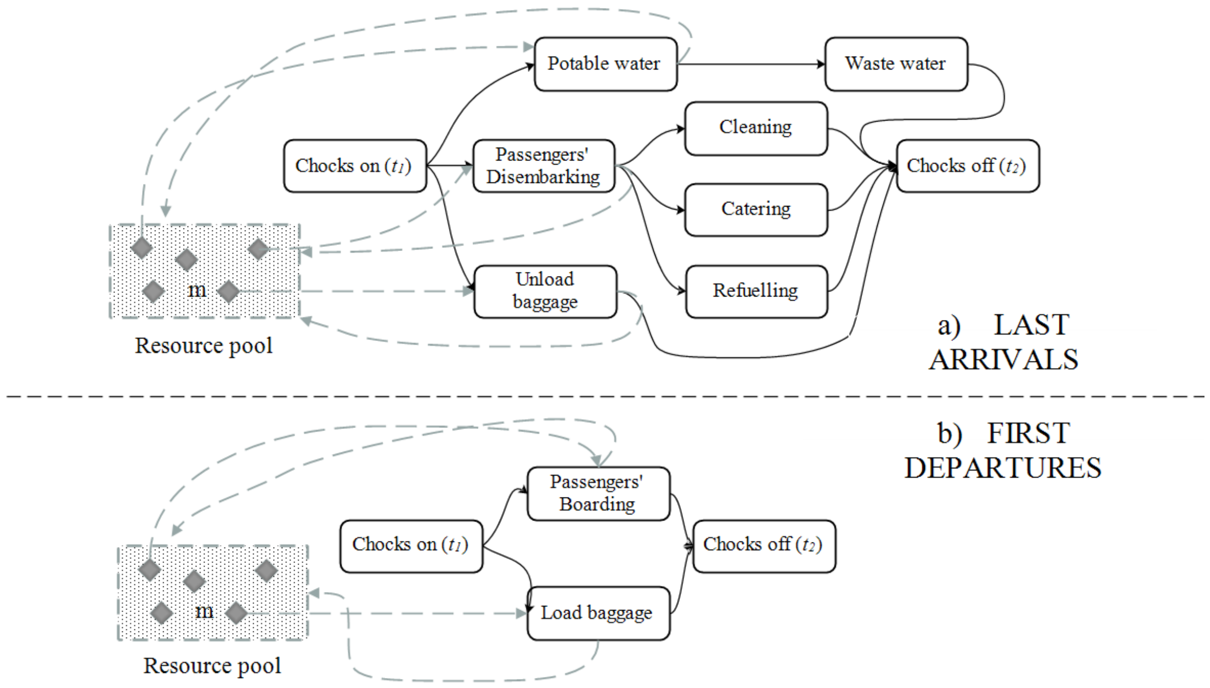


Figure 5.7. Turnaround activities and operations included in the model

Let O_m be the set of operators of ground handler *m* in service. Available operators *j* are the ones contained in the grey pool in Figure 5.6. Each operation o_i is performed by one or more operators $j \in O_m$, where $j=1, ..., J_m$. Once the operation is performed, operator *j* returns available and can perform the subsequent operation. If an operation is due to begin and O_m is empty, the operation is put on hold until one or more operators j needed to accomplish it are available. Similarly, resource re_i - such as catering vehicles, fuel tank, stairs - have to be available to perform the operation *i*, as they are assumed to be limited in number.

Turnaround time $TAT_k(m|J_m)$ of aircraft k_A serviced by ground handler *m*, with *Jm* available operators, is computed as the difference between the "chocks-off time" $t_{2k}\,(m|J_m)$ and "chocks-on time" $t_{1k}\,(m|J_m)$:

$$TAT_k\ (m|J_m) = \sum_i t_{oi} = t_{2k}\ (m|J_m) - t_{1k}\ (m|J_m) \qquad \text{(Eq. 5.5)}$$

In the baseline scenario, daily operations are carried out as specified in the schedule and possible delay generally is not due to ground operations inefficiencies. In this scenario, turnaround time is the minimum time required to accommodate the aircraft and prepare it for the following flight.

In the present model, no personnel rotation is considered and the size of J_m is assumed to be constant over the entire day. This simplification derives from the assumption that criticalities appear during peak periods, when the maximum number of personnel is usually operating. During uncongested periods, some operators will remain idle as turnaround operations require anyway a minimum basic time which does not depend on the staff performing them.

5.3. Base performance evaluation

In the absence of disruptions, daily operations are carried out exactly as specified in the schedule. The performance of the airport system in the base scenario is evaluated by examining three different indicators, namely:

1) Number of flights departing late N_L
2) The total number of flights processed, N_{TOT}
3) Average Throughput Rate
4) Average Turnaround Time

The assumption is made that there is no arrival delay, which is defined as the difference between the Scheduled Time of Arrival (*STA*) in the flight schedule and the time the flight touches down in the simulation model (Actual Time of Arrival *ATA*):

$$ATA = STA \qquad \text{(Eq.5.6)}$$

In the absence of disruptions, daily operations are carried out exactly as specified in the schedule and no delay should occur. Therefore, the number of flights departing late (N_L), or late departures, should be equal to zero.

N_{TOT} is the total number of flights processed by the airport *A(R,S,M,CAP)* during the period of analysis *T*, i.e. the total number of movements:

$$N_{TOT} = N_{DEP} + N_{ARR} \ [flights] \qquad \text{(Eq.5.7)}$$

Where N_{DEP} is the number of departing flights and N_{ARR} is the number of arriving flights.

The Effective Throughput *ET* of airport *A(R,S,M,CAP)* is defined as the number of effectively processed flights (arrivals and departures) during the hour *t*, i.e.:

$$ET_{A,t} = \sum_{t=1\ hour} n_{DEP} + n_{ARR} \ \left[\frac{movements}{hour}\right] \qquad \text{(Eq.5.8)}$$

Where n_{DEP} and n_{ARR} are, respectively, flights effectively departed and landed at the airport during the hour t. The effective throughput $ET_{A,t}$ takes the value of 0 when one hour is passed, and it is recomputed for the successive hour.

In the reference scenario, the Effective Throughput is usually lower than or at most equal to the airport capacity CAP_A. The graph in figure 5.8 shows the trend of the cumulative airport capacity CAP_A (in red) and the effective airport throughput ET_A (in blue, dashed) for a generic airport A during the period of analysis T.

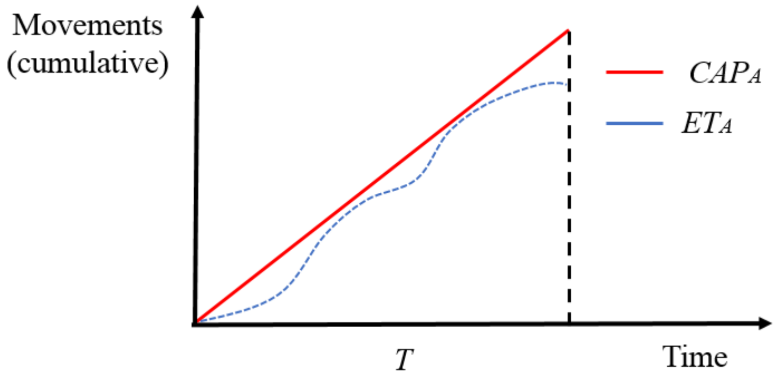


Figure 5.8. Service rate of a generic airport. Adapted from (Janić, 2015)

The Effective Throughput Rate ETR_A is then defined as:

$$ETR_{A,t} = \frac{ET_{A,t}}{CAP_A} \quad \text{(Eq.5.9)}$$

Where $0 \leq ETR_A \leq 1$.

The Average Throughput Rate ATR_A is then defined as the average of the Effective Throughput Rate ETR_A during the period of analysis T (in hours), i.e.:

$$ATR_A = \frac{\sum_T ETR_{A,t}}{T} \quad \text{(Eq.5.10)}$$

The indicators proposed above are indicative of the performance in terms of processed flights. However, inefficiencies should arise also at the turnaround level. Thus, also the average turnaround time of ground handler m over the period of analysis T is evaluated:

$$\overline{TAT}\ (m|J_{mP}) = \frac{1}{K_A} \sum_{k=1}^{K_A} TAT_k\ (m|J_{mP}) \quad \text{(Eq.5.11)}$$

This indicator expresses inefficiencies at the level of turnaround operations, which may or not result in departure delays. In fact, delays in turnaround operations may be eventually adsorbed by buffer times which are often included in the schedule (Malandri et al., 2019; Wu & Caves, 2004).

5.4. Disrupted scenario model

In the third step, the disruption scenario is modelled, in which a disruptive event undermines the correct functioning of airport operations.

Airside operations can be (and have been) affected by unexpected disruptions very different from each other. From the analysis of airport disruptions described in Chapter 4, more than 100 different disruptive events have been identified. Every disruption is unique in itself and affects airport operations in various ways. For example, an industrial action undertaken by ground handling operators is very different to model with respect to a problem with landing systems. Therefore, each disruption should be modelled differently.

However, some disruptions' clusters have been defined (see Chapter 4) depending on the operations is directly affected. Specifically, the disruptions have been clustered in 4 groups, i.e.:

A. Reduced landing or take-off capacity (e.g. radar problems)
B. Reduced runway capacity (e.g. broken aircraft on runway)
C. Reduced ground operations capacity (e.g. staff strikes)
D. Temporary closure of the airport (e.g. fires/volcanic eruptions)

Disruptions belonging to the same cluster operate, even if intrinsically different, "hit" the same airport process. Thus, a disrupted model is built for each of the clusters, separately. The four models are described in the following Sections 5.4.1, 5.4.2, 5.4.3 and 5.4.4, respectively.

In all four models, a disruption occurs at time t_1, impacting the performance of the operations at airport *A(R,S,M,CAP)* in a specific way (see figure 5.9). The disruption is cleared at time t_2. This is generally also the time in which the performance level is the lowest. The disruption - referred to as $D(t_d)$ – has a duration t_d defined as the time between the occurrence of the disruptive event and the moment in which the disruption is cleared:

$$t_d = t_2 - t_1 \qquad \text{(Eq. 5.12)}$$

Then, the system requires an additional time to return to the original configuration and the system base performance is restored at time t_3.

The time required to return to the original configuration, after that the disruption has been cleared, is referred to as recovery time t_r:

$$t_r = t_3 - t_2 \qquad \text{(Eq. 5.13)}$$

Then, the time of deviation t_t is defined as the total time from the occurrence of the disruption to the moment in which the system returns to the reference configuration (base scenario):

$$t_t = t_3 - t_1 = t_d + t_r \qquad \text{(Eq. 5.14)}$$

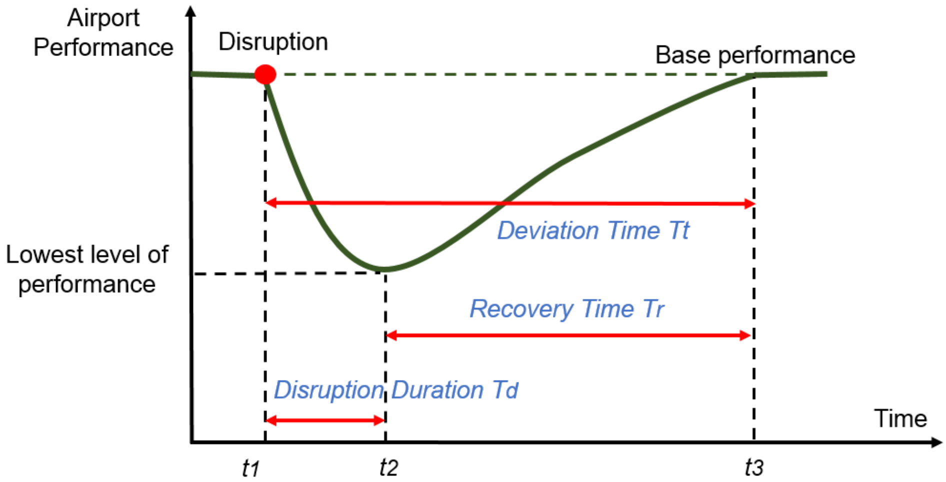


Figure 5.9. Disruption impacts and terminology

Moreover, in all models, the following assumptions are made:

i. if a flight k_A *(a,m,w)*, during the approaching phase, has to wait for more than $t_{diverted}$ minutes for landing, but no slot is available, it is diverted to an alternate airport;

ii. if a flight k_A *(a,m,w)* experience a delay higher than $t_{cancelled}$ with respect to its *STD*, it is cancelled.

5.4.1. Cluster A: reduced landing/take-off capacity

The first cluster includes all those disruptions which cause a reduction in the approaching and landing capacity, as well as take-off and climbing capacity. This is the case for example of radar problems and issues with the instrumental landing system, as well as thunderstorms.

When a disruption belonging to this cluster affect the operations at airport *A(R,S,M,CAP)*, airport's hourly capacity CAP_A is reduced by a certain percentage *RED (%)*.

Thus, and the airport's hourly capacity under disrupted conditions $CAP_{A,D}$ becomes:

$$CAP_{A,D} = CAP_A * (1 - RED) \quad \text{(Eq. 5.15)}$$

If the number of hourly movements, have reached the capacity CAP_A of airport *A(R,S,M, CAP)*, that is if:

$$ET_{A,t} = CAP_{A,D} \quad \text{(Eq. 5.16)}$$

the airport cannot handle any other landing or take-off during the hour *t*. Thus, approaching aircraft have to hold on air until the next hour to land; similarly, departing aircraft have to wait until the successive hour to take-off.

This means that the reduced capacity is too low to process the scheduled flights according to the schedule, and some delay will occur. Otherwise, if the reduced capacity is still enough to handle the traffic at the affected airports, no delay will be experienced, and departures will occur according to their schedule.

5.4.2. Cluster B: Reduced runway capacity

The second cluster includes disruptions related to the availability of runways and taxiways. For example, if the runway is not available because of an incident, or because of holes on the runway or taxiway.

In this scenario, arriving and departing aircraft cannot use the disrupted runway *r* and they are all rescheduled to use different runways. Also in this case, delays are caused by capacity constraints. If the airport has a single runway, then aircraft cannot land neither depart until the end of the disruption.

In this scenario, congestion on the remaining runways increase and may cause delays. In fact, aircraft have to wait clearance of the runway, including the time needed for vortices to dissolve (t_{vortex}).

5.4.3. Cluster C: Reduced ground operations capacity

The third group refers to disruptions affecting ground operations, for example ground operators' industrial actions or broken vehicles.

The modeling of this cluster can be different strongly depends on the disruption type. Two main cases can present:

1. Industrial action of ground handlers' operators;
2. Technical failure related to turnaround operations.

If the disruption is the case of an industrial action of ground handlers m' operators, the number of available operators J_m is reduced of a certain percentage $P_{m,d}$ and the number of available operators becomes:

$$J_{m,d} = J_m * (1 - P_{m,d}/100) \quad \text{(Eq. 5.17)}$$

As a consequence, turnaround time may increase, propagating over the day and causing late departures. When industrial actions are called, usually not the entire staff agrees and the percentage of operators on strike may be different from strike to strike.
Otherwise, if the disruption is caused by a technical failure, for example by the failure of a fueling vehicles or by the absence of the de-icing liquid, aircraft are not serviced until an alternative resource is available or until the disruption is cleared.
Then, this cluster is modeled case by case.

5.4.4. Cluster D: temporary closure of the airport

In the last group, we refer to disruptions causing the complete closure of the entire airport for a certain period of time. This is the case of evacuations due to security alert or fires, or the case of power failure.
In this all the operations are put on hold. Aircraft cannot land neither depart and turnaround operations are stopped. In this case, the airport's hourly capacity under disrupted conditions $CAP_{A,D}$ becomes:

$$CAP_{A,D} = CAP_A * 0 = 0 \quad \text{(Eq. 5.18)}$$

5.5. Disrupted performance evaluation

The disruptive event occurring at time t_1 causes a degradation of the service from the standard baseline value. In the fourth step of the analysis, the impact caused by the disruption on airport airside operations is evaluate as the variation of selected performance indicators between the disrupted and base (reference) scenarios is evaluated. The higher the variation, the higher are the impacts of the disruptive events at the considered airport.

In the context of airport operations, performance is usually evaluated in terms of delays. Therefore, the impacts generated by a given disruptions are evaluated in terms of:

1) Total number of flights departing late N_L
2) Total and average departure delay $DEL_{DEP,TOT}$ and $\overline{DEL}_{DEP}$

3) Total and average arrival delay $DEL_{ARR,TOT}$ and $\overline{DEL}_{ARR}$
4) Total number of cancelled flights N_C
5) Total number of diverted flights N_D

Moreover, the performance indicators computed for the base scenario (Section 5.3) are compared to the ones in the disrupted scenario. Thus, impacts are evaluated also in terms of:

6) Variation in Average Turnaround Time
5) Difference in Average Throughput Rate

First of all, impacts are evaluated in terms of departure delay. It is assumed that a flight is departing late if its actual time of departure (ATD_k) is higher than the scheduled "off-block" time, i.e.:

$$ATD_k \geq STD_k + 15\ min \qquad \text{(Eq. 5.19)}$$

The last term of Eq. (5.19) derives from the delay definition adopted, which is the one used by EUROCONTROL, according to which a delay occurs if any activity fails to begin within fifteen minutes after the expected start time (EUROCONTROL, 2018b). Then, the delay of the departing flight $k_A\,(a,m,w)$ is:

$$DEL_{DEP,k} = ATD_k - STD_k\ [minutes] \qquad \text{(Eq. 5.20)}$$

The total number of flights departing late N_L is given by the sum of all flights departing with a delay longer than 15 minutes during the entire period of analysis T:

$$N_L = \sum_T k_A\ (a, m, w | DEL_{DEP,k} > 15) \qquad \text{(Eq. 5.21)}$$

The total and average departure delay, $DEL_{DEP,TOT}$ and $\overline{DEL}_{DEP}$ respectively, are given by:

$$DEL_{DEP,TOT} = \sum_{N_L} DEL_{DEP,k} \qquad \text{(Eq. 5.22)}$$

$$\overline{DEL}_{DEP} = \frac{DEL_{DEP,TOT}}{N_L} \qquad \text{(Eq. 5.23)}$$

Similarly to departure delays, a flight $k_A\,(a,m,w)$ is assumed to arrive late if its actual time of arrival (ATA_k) is higher than the Scheduled Time of Arrival (STA_k) of more than 15 minutes:

$$DEL_{ARR,k} = ATA_k - STA_k > 15\ minutes \qquad \text{(Eq. 5.24)}$$

And the total ($DEL_{DEP,TOT}$) and average ($\overline{DEL}_{DEP}$) arrival delays are:

$$DEL_{ARR,TOT} = \sum_{N_{ARR,L}} DEL_{ARR,k} \qquad \text{(Eq. 5.25)}$$

$$\overline{DEL}_{ARR} = \frac{DEL_{ARR,TOT}}{N_{ARR,L}} \qquad \text{(Eq. 5.26)}$$

Where $N_{ARR,L}$ is the total number of flights arriving late at airport *A(R,S,M,CAP)* during the simulation period *T*:

$$N_{ARR,L} = \sum_{T} k_A \; (a, m, t | DEL_{ARR,k} > 15) \qquad \text{(Eq. 5.27)}$$

Moreover, disruptions generally cause flight cancellations or diversions, as specified in Section 5.4. Then, impacts are evaluated also in terms of total number of cancelled flights N_C and total number of diverted flights N_D during the period of analysis *T*. The total impact *TI* is defined as the total number of flights impacted by the disruption, including delayed, cancelled and diverted ones:

$$TI = N_L + N_D + N_C \; [flights] \qquad \text{(Eq. 5.28)}$$

During the disruption period, usually a degradation of the scheduled system service rate is experienced and the Effective Throughput $ET_{t,D}$ of airport *A(R,S,M,CAP)* decreases during the deviation time t_t. The disrupted Average Throughput Rate $ATR_{A,D}$ is computed according to Equation 5.10, considering as period of analysis the time of deviation t_d

$$ATR_{A,D}(t_t) = \frac{\sum_{tt} ETR_{A,D,t}}{t_t} \qquad \text{(Eq. 5.29)}$$

Where $ETR_{A,D,t}$ is the disrupted Effective Throughput Rate. Then, the variation is computed as the difference between the disrupted and baseline indicators during the deviation time, it is referred to as *Capacity Loss CL*:

$$CL = ATR_A(t_t) - ATR_{A,D}(t_t) = \frac{\sum_{tt} ETR_{A,t}}{t_t} - \frac{\sum_{tt} ETR_{A,D,t}}{t_t} \qquad \text{(Eq. 5.30)}$$

Similarly, the Average Turnaround Time $\overline{TAT}_D$ in the disrupted scenario is evaluated and compared to the one in the baseline scenario. The variation is referred to *Turnaround Loss TL*:

$$TL = \frac{\overline{TAT}_D \; (m | J_{mP}) - \overline{TAT} \; (m | J_{mP})}{\overline{TAT} \; (m | J_{mP})} \qquad \text{(Eq. 5.31)}$$

This last indicator allows to determine is disruptions affect or not turnaround operations. In the latter case, the turnaround time does not increase, and delays might be result from infrastructural and capacity constraints; otherwise, if important delays show during turnaround operations, additional resources should be deployed to reduce inefficiencies at the ground operations' level.

5.6. Resilience and vulnerability indicators

In last step, indicators are proposed to determine both the vulnerability and resilience of the system at a specific disruption.

As discussed in Chapter 1, the term ''vulnerability'' refers to the susceptibility of a system to experience severe performance impacts in consequence of exceptional disruptions. The vulnerability indicator should reflect the magnitude of the deviation of the afore-mentioned indicators from the targeted system performance level, that is the amount of performance loss.

In the context of airport operations, performance loss is strictly related to the amount of delay. In general, the delayed flights impose important economic losses on airlines, airport operators and passengers. The significative impacts of disruptions have been discussed previously in Chapter 4. For this reason, flights delays, cancellations and diversions are assumed as indicators of performance for the airport operating under disruptive conditions.

In particular, vulnerability *V* of airport *A(R,S,M,CAP*) to the disruption *D(td)* is evaluated as the weighted sum of delayed, cancelled and diverted flights:

$$V_{A,D} = \beta_L N_L + \beta_D N_D + \beta_C N_C \qquad \text{(Eq. 5.32)}$$

and weights are evaluated with respect to the cost of a cancelled flight $COST_C$:

$$\beta_L = \frac{COST_L}{COST_C} \qquad \text{(Eq. 5.33)}$$

$$\beta_D = \frac{COST_D}{COST_C} \qquad \text{(Eq. 5.34)}$$

$$\beta_C = \frac{COST_C}{COST_C} = 1 \qquad \text{(Eq. 5.35)}$$

Where $COST_L$ and $COST_D$ are the costs of a delayed and diverted flight, respectively. This definition of vulnerability takes into consideration the costs of delays, cancellations and diversions (exposed in Section 4.3). In other words, vulnerability is evaluated as the number of equivalent cancelled flights during the period of disruption, where weights correspond to costs.

The loss is expressed in terms of the proportion of original system functionality (performance) retained immediately post-event, that is the percentage of impacted flights with respect to the scheduled one during the deviation time t_d.

Besides, while the vulnerability indicator measures how far the quantity of interest deviates from typical values the resilience indicator should also include system's ability to recover in the most efficient ways. Here, resilience is defined as "*the airport's ability, during and immediately after the occurrence of a disruptive event, to reduce efficiently both the magnitude and duration of the deviation from targeted operational performance levels*". Thus, resilience should consider both the magnitude of the deviation and how effective is the recovery phase is, i.e. how fast the system is capable or returning to the original configuration.

Based on this definition, resilience is evaluated as a function of the *Capacity Loss CL* and of the total duration of the disruption, including the recovery time. Specifically, resilience is evaluated as the average loss of capacity normalized throughout the deviation time t_d:

$$RES = \frac{CL}{t_t} = \frac{ATR_A(t_t) - ATR_{A,D}(t_t)}{t_t} \qquad \text{(Eq. 5.36)}$$

Specifically, the total impact is expressed as the unitary loss of capacity during the total disruption period t_t.

6. IMPLEMENTATION

6.1. Airport simulation

Airport operations rely on a complex architecture, in which various agents and facilities interact with each other (Ashford et al., 2013), creating a complex combination of interconnected processes. Most elements in the network are subject to uncertainties, making airside operations a stochastic phenomenon (Rodríguez-Sanz et al., 2018). The stochastic and time-varying nature of the operations create a set of dynamics which influence the way the system evolves and how airlines and airport service providers and operators manage their operations. This is even more emphasized when the airport is operated within small limits of its capacity.

In case of unexpected airport disruptions, it is likely that consequences with non-linear impacts arise (Damgacioglu et al., 2018). Because of the interconnectedness of arrivals, departures and the processes in the between, delay dynamics and their propagation constitute a core element when analysing airport's performance. Because of the dynamic and stochastic nature of airport operations, delays propagate among operations with a non-linear behaviour, often causing spill-over effects which spread throughout the entire air network.

Given the inherent complexity of the airport system, its dynamic and stochastic behaviour, and the intrinsic variability of the delay propagation problem, simulation has been considered the most appropriate method for assessing the airport system's time-varying performance and analysing the effects of unforeseen events.

Simulation techniques provide the opportunity to combine a remarkable large variety of elements for expressing the behaviour of a sociotechnical systems, including performance variability of the interacting agents. By using simulation, the inherent complexity and stochasticity of the airport system can be comprehensively described in unravelled, thus providing tools and insights which may facilitate the design and assessment of strategies to reduce poor outcomes and to support the system's full functioning.

Simulation is nowadays used in a variety of fields and industries, often combined with optimization techniques, to deal with decision-making problems (Mota & Flores, 2018). It allows to cope with real-world problems safely and efficiently, by providing clear insights into complex systems.

Simulation modelling offers a wide number of advantages with respect to traditional modelling techniques.

First, simulation models allow to analyse systems and find solutions where methods such as analytic calculation and linear programming fail. This is the case of complex systems where elements interact with non-linear behaviour.

Second, simulation models have the ability to solve operational problems where stochasticity is a critical component, as uncertainty in operations can be easily represented.

Third, simulation provides an environment for studying the dynamic behaviour of a system which operates under different uncertain conditions, by means of continuous, discrete or hybrid models. Differently from solver-based analytics, or spreadsheets, it allows to observe the behaviour of a system over time, by tracking entities and values within the level of abstraction chosen.

Fourth, once developed, verified and validated, simulation models have proved to be useful for exploring and examining alternative operating scenarios and different system configurations. Potential changes can be simulated in order to answer a wide range of "what-if" questions and to predict the impact of such changes on the system's performance. Simulation is useful also to support the system's design phase and to study such systems before they are built. Furthermore, they provide a method of analysis that can be easily verified, communicated and understood.

Hence, simulation techniques can be used both as an analysis tool for predicting the effects of changes to existing systems, and as design tool to predict the performance of new systems under varying sets of circumstances.

Also in the aviation industry, simulation is an approach that several researchers and stakeholders have been recently exploring (Mota, 2015). Due to economic importance and complexity of airport operations, simulation technologies are becoming of fundamental importance and have been often used in airport daily operations management, planning and design.

Over the last two decades, numerous studies have been proposed in the literature in which macroscopic and microscopic simulation models have been developed for studying airport airside operations and the interaction with existent infrastructure (Martinez et al., 2001). In fact, analytical models, despite being good in the planning stage, do not evaluate incorporated stochastic flight delays that usually incur in the case of real-time operations (Yan et al., 2002). Due to the aforementioned advantages, the simulation approach seems to be the proper to evaluate the performance of airport system's in a close-to-reality-way, thus providing valuable support in the management and design.

A number of authors have developed various simulation models of the airport airside or, most often, of a particular subsystem present in it, for example the runway system or a specific ground handling operation. These models are usually used to analyse the operational efficiency of the system or assess the impacts resulting from different scenarios (Li & Chen, 2018).

Some studies focus on the aircraft in the runway-taxiway-apron system inside the aerodrome, and the evaluation of the flight delay level, taxiing time, take-off and landing efficiency, and the ground operating capacity at an airport. For example, (Martinez et al., 2001) use discrete-event simulation to model runway operations at airport, by using the simulation software STROBOSCOPE. (Bubalo, & Daduna, 2011) use the simulation tool SIMMOD to estimate the infrastructure workload of Berlin-Brandenburg International airport deriving from different demand time patterns and changing traffic mix. The same software is used (Schinwald et al., 2016) to determine airport capacity and simulate the airport response to increasing air traffic demands. (Mota et al., 2014) use the discrete-event simulation software SIMIO to assess the potential capacity problems for a future airport. The work of (Zuniga et al., 2011) take the perspective of the air traffic controller for improving the throughput in the terminal manoeuvring area of an airport using simulation and optimization. Cheng (1998) proposed a network simulation model to solve pushback conflicts in apron taxiways. (Chen et al., 2015) developed a simple simulation model for strategic planning of the ground the ground network of an airport. (Yan et al., 2002) propose a simulation framework to analyse gate assignment. include the interrelationship between static gate assignment and real-time gate assignment affected by stochastic flight delays that occur in real operations. (Khammash et al., 2017) propose a micro simulation approach to assess aircraft ground movements and estimate taxi times; they use the generic simulation software AnyLogic.

In addition, extensive research has been conducted to simulate ground handling operations. For example, Wu and Caves (2002) develop a model to simulate aircraft rotation in a multiple airport environment, including delays due to operational inefficiencies modelled as stochastic variables. (Wu & Caves, 2004) use of Markov chains together with Montecarlo simulation for investigating turnaround performance. Many works use simulation to deal with the resource allocation problem. For example, (Voulgarellis et al., 2005) propose an airport ground handling simulation model by using MATLAB to determine the amount of ground service equipment required for a specific flight plan. In (Vidosavljevic & Tosic, 2010), a model of the aircraft turnaround process at aprons is developed using a Petri nets approach, in order to investigate its sensitivity to arrival delays and to determine the number of required ground service equipment. Generally, the modelling techniques adopted are microscopic models built by means of discrete event or agent-based simulation. For example, (Norin et al., 2012) use the commercial software Arena to model all processes from touch-down to taxi-out at Stockholm Arlanda airport, with a particular focus to the de-icing process. In (Adeleye & Chung, 2006), discrete event modelling is used for modelling and investigating bottlenecks in turnaround processes. Similarly, a detailed model of the turnaround operations at Lelystad airport was developed by (Mota et al., 2017) by using SIMIO. In (Bevilacqua et al., 2015) Delphi methodology and discrete event simulation are used to define and analyse the current state of the ground handling processes of an Italian airport and to design a future state of these processes focused on improving service quality and workflow. They use the simulation software ProSim.

Most studied often focus on selected ground handling operations, which is indicative of the complexity of the process, such as cargo and baggage loading and unloading (Malandri et al., 2018) or passengers' boarding and de-boarding processes. For example, in (Schmidt et al., 2016; Schmidt et al., 2017) a simulation model of the passenger boarding process is developed. The model allows to analyse different boarding scenarios and evaluated passenger congestion at the aircraft door, by taking into account different aircraft configurations and various types of separation while boarding.

It is therefore evident that the advantages and potential of simulation techniques are increasingly recognized in the context of airport operations. Several models have been developed which analyse different airside operations, use various software and different modelling techniques.

The principal modelling techniques which can be used in simulation modelling are described in the next Section 6.2.

6.2. Simulation modelling techniques

Nowadays, three different modelling techniques exists which can be used in simulation models, and each of them serves a specific range or abstraction level: System Dynamics (SD), Agent-Based (AB) or Discrete-Event modelling (DE). Each method serves a specific range of abstraction level and is more suitable to model certain real-world system instead of others.

System dynamics modelling represents the real-world processes in terms of stocks, e.g. knowledge, people, money, flows between these stocks and information that determines the values of the flows. System Dynamics abstracts from single events and agents, focusing on an aggregate view. It is used for systems in which the state variables change continuously in time, which can be for example the level of a tank. This modelling approach is used mainly in long-term, strategic models and assumes a high level of aggregation, in which single entities lose their individual properties, histories or dynamics.

Agent-based is a relatively novel approach in which the power of computers is used simulate independent behaviour and decision making of the entities within a system. It can be described as decentralized, individual-centric approach to model design. With this modelling approach, each agent, put in a certain environment, has a determined behaviour and establishes connections with other agents. The system-level behaviour results from the interaction of many individual behaviours. The level of abstraction can vary from highly abstract models where agents represent governments or companies, to very detailed models where agents represent physical objects.

Discrete Event modelling is a paradigm which suggests approximating real-world processes by considering only certain events – or "important moments" in the system lifetime. This modelling approach is suitable for analysing systems in which entities proceed along an identifiable sequence of processes interlinked between them. Variables' states do not change continuously but, rather, they change at particular instants of time, based on the occurrence of events and the evolution of those processes. In a narrower sense, Discrete event is also to indicate "process-centric" modelling, in which the system is described as a flowchart. Discrete event modelling supports medium and medium-low abstraction.

In figure 6.1, the relationship between each modelling approach and the corresponding level of abstraction is illustrated.

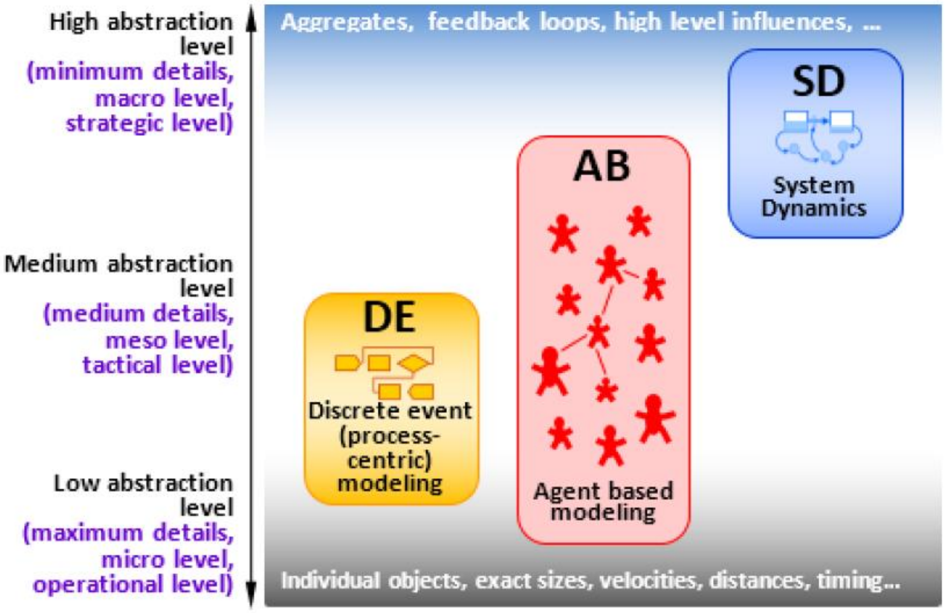


Figure 6.1. Level of abstraction of each modelling approach. Source: (Grigoryev, 2017)

In the case of the airport airside system, it is appropriate to describe the behaviour of the system by considering the entities that populate the system – i.e. aircraft – as elements that passively undergo the appropriate sequence of operations, represented by events that succeed one another over time in the form of chains and sequences of processes. In other words, both LTO and turnaround operations can be considered as an ordinate sequence of steps that each aircraft undergo at the airport (Postorino & Mantecchini, 2020). Each entity (aircraft), proceeding through the system, reaches a process element, enters a queue, occupies a resource, if available, for a specific service time and, when the service is completed, the entity releases the resource and leaves the process element. For this reason, the Discrete Event modelling approach is considered to be the best tool for the representation of the system under analysis and it is adopted to model LTO cycle and turnaround operations. Moreover, with a DE modelling, simulations run faster with respect to the case of Agent-based modelling, which make DES a good approach for the development of the airside operation simulation model.

6.3. Software used for implementation

The model described in previous Chapter 5 has been implemented by using the generic simulation software AnyLogic (www.anylogic.com), developed by The AnyLogic Company (former XJ Technologies). While commercial software provide a set of limitations regarding the customization of a simulation model, the use of a general-purpose software allows to obtain an unlimited flexibility regarding the construction of the model.

AnyLogic is a simulation tool which supports interactive 2D and 3D animation and which is widely used by a large number of industries in different fields, including transportation, supply chains, warehouse operations, manufacturing and others. It supports the three main simulation methodologies:

- System Dynamics (SD)
- Discrete Event Modelling (DE)
- Agent Based Modelling (AB)

In AnyLogic, it is allowed to combine these simulation approaches within the same model.

The AnyLogic simulation language consists of four main items:

- Flow and stock diagrams: are used when modelling with System Dynamics;
- Process flowcharts: constitute the base of Discrete Event simulation.
- Statecharts: are principally used in Agent-based modelling, but also for discrete-event simulations. They are used to define agents' behaviour;
- Action charts: are used to define algorithms;

The software, developed in a Java environment, has an articulated graphical interface that facilitate the development of complex models and the interaction between different modelling techniques. In addition to the graphical modelling language, AnyLogic allows the user to implement additional java code to extend the simulation model.

AnyLogic includes a series of libraries, which contain a set of predefined processes elements - called "objects" – used to represent the different types of processes. The presence of libraries facilitates and speeds up the programming, for example by providing specific tools for dealing with rail transport systems or for processing complex algorithms. Each object in the libraries is characterized by specific functions and properties and, to build processes, they are linked in the form of chains. The standard libraries provided by AnyLogic are:

- The Process Modelling Library, which supports discrete event simulation;
- The Pedestrian Library includes objects to simulate pedestrian flows in a physical environment;
- The Rail Library is used for simulating operations of rail yard;
- The Fluid Library allows to model storage and transfer of fluids;

- The Road Traffic Library supports the simulation of vehicle traffic roads and includes objects such as traffic lights, pedestrian crossing and parking lots;
- The Material Handling Library assists warehouse and factories simulation.

In the case of discrete event modelling, the model is specified graphically as a process flowchart where operations are represented by “blocks”.

The flowchart typically starts with “*source*” blocks, in which entities are generated and injected into processes, and ends with “*sink*” blocks that remove them from the simulation environment. An entity – or agent - is a unit of model that can represent people or objects, such as clients, patients, physical and electronic documents, parts, products, pallets, vehicles, or many other things including projects, phone calls, ideas, organizations. Entities can have behaviour, memory, timing, contacts and so forth. The entities, once generated, will pass through the “blocks” of the flowchart, undergoing the different operations. For each block it is also possible to define, by means of appropriate commands, operations to be performed at the entrance and exit of the entity.

Resources are objects that provide a service to the entities, imposing on them a time delay whose extension depends on the duration of the service used and the waiting time necessary to access the necessary resources. They may represent staff, doctors, operators, workers, servers, computer memory, transport and so forth. In classic discrete event tools, the entities are passive and can only have attributes that affect the way they are handled; besides, in AnyLogic, entities and resources can be modelled as agents with individual behaviour and state changes. Service times and entities arrival times are usually stochastic, and since they’re drawn from a probability distribution, discrete event models are themselves stochastic. In simple terms, this means a model must run for a specific amount of time or complete a specific number of replications before it produces meaningful output. To build the flowchart, the Process Modelling Library is used, which contains objects to model entities, processes and resources. Typical output expected from a discrete event model include: utilization of resources, time spent in the system or its part by an agent; waiting times; queue lengths, system throughput, bottlenecks.

As specified in previous Section 6.1, in this work the discrete event modelling approach is adopted. To implement the model, the principal objects used belong to the Process Modelling Library and include[1]:

- Source: generate agents;
- Sink: disposes incoming agents;
- Delay: delays agents by the specified delay time, which can be deterministic, stochastic or defined by certain events during the simulation;
- Queue: stores agents in the specified order;
- Hold: blocks or unblocks the agents flow;
- SelectOutput: forwards the agent to one of the output ports, depending on probabilistic or deterministic conditions;
- Match: finds a match between two agents from different inputs, then outputs them.

In addition, several other objects are used to implement the model. A comprehensive description of all elements used in the simulation model is provided in Appendix A.

6.4. Description of the simulation model

6.4.1. Airport layout and attributes

As first step of the implementation phase, the layout of the airport airside area has to be detailed. Airports are very different from each other. They have different dimensions, runway configurations, different infrastructural features, different number of operators and resources and each characteristic influences the aerodrome performance.

Each generic airport *A(R,S,M,CAP)* is characterized by the following attributes:

- Airport airside layout
- Number and configuration of runways;
- Capacity *CAP*;
- Number of aprons;
- Number of parking stands (total and per apron);
- Number of ground handlers;
- Number of operators and resources per ground handler;

[1] Definitions retrieved from AnyLogic Simulation Software Help

The airport airside layout is implemented in the model as an image, over which the network of runways and taxiways are built. The airside network is composed of nodes, where operations effectively take place, and paths, which are used by entities to move from one node to another. Each path is attributed a length, which is the distance between the two connected nodes. In this model, each path can be unidirectional or bidirectional.

The capacity of airport *A(R,S,M,CAP)* is evaluated in accordance to equation 6.1:

$$CAP_A = CAP_{A,DECLARED} * \alpha \left[\frac{movements}{hour}\right] \quad \text{(Eq. 6.1)}$$

Where α is assumed to be equal to 1.1.

The runway path is considered to be unidirectional and with a limited capacity of 1, i.e. no simultaneous aircraft occupancy is allowed on the runway. Furthermore, if there are restrictions regarding the use of the runway, they are implemented. For example, the following restrictions may be present:

- Some runways do not have the requirements to handle wide-body aircraft; then, only narrow-body aircraft are assigned to these runways;
- At some airports, runways can be used only in determined directions for reasons related to various factors including environment, noise, security and others;
- At some airports, certain runways cannot be used simultaneously;
- At some airports, certain runways are used only for landing, while some others only for take-off;
- Certain runways cannot be used during night periods.

Aprons are implemented as nodes with a limited capacity equal to the corresponding number of stands. When an aircraft arrives at the apron occupies one stand, and the available capacity of the apron decreases. If all stands are occupied, the aircraft cannot enter the apron.

6.4.2. Arrivals and departures schedule

Aircraft are generated in the airport's local airspace according to a schedule. To each arriving flight, a departure time is associated. Inbound and outbound movements are linked by matching the tail number of the aircraft, or aircraft registration number, which is unique to a single aircraft. By using the tail number, it is possible to model the rotation of the aircraft and determine the successive departures during the period of analysis *T*.

The schedule includes the following data:

1. Arrival date and scheduled time of arrival *STA*
2. Arriving flight number
3. Airline *a*
4. Ground handler *m*
5. Arriving aircraft tail number
6. Aircraft type *w*
7. Type of flight
8. Originating airport for the inbound flight
9. Departure date and scheduled time of departure *STD*

The parameter "Aircraft type" indicates if the aircraft is narrow or wide body. The parameter "Type of flight" is used to indicate if the flight has both scheduled arrival and departure during the period of analysis, of if otherwise it is a "*first departure*" or one "*last arrival*". It the flight do not have any scheduled arrival before its *STD*, then it is a first departure and the parameter "Type of flight" assumes the value 1. If the flight does not have any other scheduled departure during the period of analysis, it is classified as "*last arrival*", indicated with the number 3. Otherwise, "Type of flight" is equal to 2.

Table 6.1. summarized the input parameters necessary to implement the model, regarding both the airport and the schedule, indicating also the type of parameter.

Despite the peculiarity of each airport and schedule, the model should be as flexible as possible in order to adapt it in a fast manner to different airports. Therefore, several assumptions are made in order to increase the flexibility and ease of use of the model, while maintaining the integrity and accuracy of the results. Some of the major assumptions used in the model are listed below:

(1) If certain runways are not adequate for handling wide-body aircraft, they are used for landing and take-offs of narrow-body aircraft; otherwise, aircraft are assigned randomly to runways;
(2) Depending on the runway used for landing, aircraft are assigned to the nearest available apron; if the apron cannot receive wide-body aircraft, only narrow-body ones will use it;
(3) Aircraft are assigned randomly to ground handlers;
(4) Air traffic mix is restricted to scheduled airline services.

Table 6.1. Data input for the simulation model

Airport		Schedule	
Parameter	**Type**	**Parameter**	**Type**
Airport airside layout	Image	**Arrival date and scheduled time of arrival *STA***	Date
Number of runways	Integer	**Arriving flight number**	String
Capacity *CAP*	Double	**Airline**	String
Number of aprons	Integer	**Ground handler**	Integer
Number of parking stands (total and per apron)	Integer	**Arriving aircraft tail number**	String
Number of ground handlers	Integer	**Aircraft type**	String
Number of operators and resources per ground handler	Double	**Type of flight**	Integer
		Originating airport for the inbound flight	String
		Departure date and scheduled time of departure *STD*	Date

6.5. Base scenario implementation

As specified in Chapter 5, the developed model consists of two hierarchical systems. At the higher level, LTO operations are modelled, as described in Section 5.2. In this level, the agent of the model is the aircraft, which undergo a sequence of processes.

Aircraft $k_A\,(a,m,w)$ are generated at the beginning of the approaching phase, in the sequence of the schedule. Arrivals are defined according to an arrivals database which specifies the schedule. Each aircraft, when generated, is assigned a series of attributed which are shown in the previous Table 6.1. Once arrived, aircraft start the approaching phase, during which the aircraft approaches the airport for a time $t_{approach}$ = *Uniform (2,3)*[1] minutes. At the end of the approaching phase, aircraft k_A *(a,m,w)* is assigned randomly to one of the runways of the airport.

Once assigned the runway, the aircraft queue for landing following a FIFO priority scheme. If the runway is free, the aircraft can start landing and occupies the runway. Moreover, A minimum time t_{vortex} must elapse between two subsequent runway utilizations. t_{vortex} is assumed to be equal to 60 seconds after narrow-body aircraft, 90 seconds after wide-body ones, in accordance with the minimum separation standards (ICAO, 2007).

The landing process when the aircraft occupies the runway and finishes when the aircraft leaves it towards to the taxiway. The runway occupancy time, i.e. the time an aircraft takes to utilize the runway, depends on the length of the runway and the deceleration of the aircraft. During the landing phase, the aircraft is assumed to have a speed of 145 knots. Then, the aircraft proceeds on the taxiway towards its assigned apron. Aircraft move on taxiways with a constant speed of 15 knots, ensuring a minimum safety distance of 60 meters from other aircraft. Taxiways and runways are represented with limited capacity and directional control.

The number of aprons depends on the aerodrome to be modelled, as well as the capacity of each apron, where capacity is the number of stands. If the assigned apron is full, the aircraft goes the nearest one until it finds one stand free. If no stands are available, the aircraft queue at the initial apron by following a FIFO scheme, until one stand becomes available.

When reached the stand, the aircraft exits from the top-level model to enter the turnaround model. One turnaround model exists for each ground handler operating at the aerodrome. The aircraft is sent to the turnaround model corresponding to its ground handler, which is specified in the attribute "*ground handler*".

At the turnaround operation level, the arriving aircraft k_A *(a,m,w)* is handled by the operators of the corresponding ground handler, by using the resources available. Aircraft are serviced according to a FIFO priority scheme and, if all operators are busy, the aircraft waits (or the operation is put on hold) until some operators are available again. Since it was not possible to know exactly the number of operators and the amount of resources of the generic airport *A(R,S,M,CAP)*, it assumed that J_m is the minimum number of workers necessary to perform turnaround operations without provoking delays in the base scenario; the same is assumed for

[1] The *Uniform (min,max)* distribution is used to represent a random variable with constant likelihood of being in any small interval between a minimum *min* and a maximum *max*.

resources. In order to make the model as flexible as possible, the duration t_{oi} of each turnaround activity is the same for all airports. These durations are stochastic and they have been determined according to previous literature (Bevilacqua et al., 2015; Mota et al., 2017; Schmidt, 2017) and aircraft manuals (AIRBUS, 2017), and validated by experts' opinions. The distributions used in the model are shown in Table 6.2.

Table 6.2. Turnaround operations' time distributions

i	Operation *i*	Sub-operation o_i	t_{oi}
1	**Chocks on**	-	30 secs
2	**Disembarking**	Stairs positioning	TRIANGULAR[1] (1.8, 2.3, 2 min)
		Passengers disembarking	20 pax/min
3	**Cleaning**	Cleaning	TRIANGULAR (13, 19.5, 16.5 min)
4	**Catering**	Catering truck connection	TRIANGULAR (0.85, 1.2, 1.05 min)
		Departure catering loading	TRIANGULAR (7, 9, 8 min)
		Arriving catering unloading	TRIANGULAR (3, 5, 4 min)
		Catering truck disconnection	TRIANGULAR (0.95, 1.3, 1.15 min)
5	**Potable Water**	Water truck connection	TRIANGULAR (0.65, 0.95, 0.8 min)
		Potable water replenishment	TRIANGULAR (4, 6, 5 min) - *Double for wide-body*
		Water truck disconnection	TRIANGULAR (0.45, 0.85, 0.6 min)
6	**Waste Water**	Waste water truck connection	TRIANGULAR (0.65, 0.95, 0.8 min)
		Waste Water	TRIANGULAR (4, 6, 5 min) - *Double for wide-body*
		Waste water truck disconnection	TRIANGULAR (0.45, 0.85. 0.6 min)
7	**Baggage/Cargo Unloading**	Loader positioning	TRIANGULAR (40, 80, 60 sec)
		Arriving baggage/cargo unloading	TRIANGULAR (5, 9, 7 min) - *Double for wide-body*

[1] The *Triangular (min, max, mode)* distribution is a continuous probability distribution with lower limit *min*, upper limit *max* and mode *mode*.

		Loader disconnection	TRIANGULAR (40, 80, 60 sec)
8	**Refuelling**	Fuel truck connection	TRIANGULAR (0.7, 1.2, 0.9, min)
		Refuelling	TRIANGULAR (7, 9, 8 min) - *Double for wide-body*
		Fuel truck disconnection	TRIANGULAR (1.0, 1.4, 1.2 min)
9	**Baggage/Cargo Loading**	Loader positioning	TRIANGULAR (40, 80, 60 sec)
		Departing baggage/cargo loading	TRIANGULAR (5, 11, 7 min) - *Double for wide-body*
		Loader disconnection	TRIANGULAR (40, 80, 60 sec)
10	**Passengers boarding**	Passengers boarding	12 pax/min
		Stairs removing	TRIANGULAR (1.0, 1.6, 1.3 min)
11	**Chocks off**	-	30 secs

When turnaround operations are completed, the aircraft returns in the higher-level model. If the serviced aircraft belongs to the “last arrivals” category, specified by the indicator “*Type of flight = 2*”, the aircraft moves to a remote apron and is removed from the simulation. Otherwise, it waits at the stand until its Scheduled Time of Departure (*STD*). Then, pushback operations can start, and they have a random duration $t_{pushback}$ of 3 to 5 minutes. Similarly to the taxi-in phase, during taxi-out aircraft move on taxiways with a constant speed of 15 knots. By using taxiways, the aircraft reaches the head of the runway, where it queues for landing according to a FIFO scheme. The runway is the generally the same runway used for landing, except from some runway utilization restrictions. If another aircraft is approaching the aerodrome, departing aircraft has to wait. If the runway is free, aircraft can take-off with an acceleration which depends on the runway length and aircraft speed (see Eq. 5.4), which is assumed to be equal to v_t=135 knots. Regarding take-offs, runway occupancy is defined as the time from when the aircraft starts its departure roll until the moment in which its wheels leave the ground. Then, the runway is available for other utilizations.

6.6. Disrupted scenario implementation

Once the base model has been implemented, the simulation model is ready to explore alternative scenarios, i.e. the disrupted ones. When the disruption starts at time t_1, some parameters of the model change according to the type of disruption. When the disruption is cleared at time t_2, the model's parameters return equal to the ones in the base scenario.

Input parameters to be changed are, depending on the disruption clusters:

- If the disruption belongs to cluster A, the disrupted hourly capacity; if the hourly movements is equal to the capacity, approaching and departing aircraft have to wait until the successive hours;
- In case of cluster B's disruptions, one of the aerodrome's runways (or taxiways) cannot be used, thus, for the duration of the disruption, aircraft cannot occupy the runway (or taxiway) path.
- Regarding Cluster C, disruptions can manifest in two different ways: ground handlers' operators or failure of ground equipment components. In the former case, the number of available operators has to be specified; in the latter situation, the reduced amount of resources.
- For disruptions belonging to cluster D, the airport hourly capacity is reduced to zero, and aircraft cannot depart neither land.

In the disruption scenarios, the following assumptions are made:

a) If an approaching aircraft has to wait for a time more than $t_{diverted}$ =45 minutes to land, the aircraft is diverted to another airport, and thus exits the simulation;
b) If an aircraft has a delay $t_{cancelled}$ higher than 180 minutes (3 hours), it is considered as a cancelled flight and thus exit the simulation model. The delay is computed at two different stages, i.e. at the end of turnaround operations, when the aircraft is at the runway head waiting for take-off.

Figure 6.2 shows the overall architecture of the simulation model in the form of a flowchart. The blocks outlined in red refer to the disrupted simulation mode. A detailed representation of the model as implemented in AnyLogic is shown Appendix A.

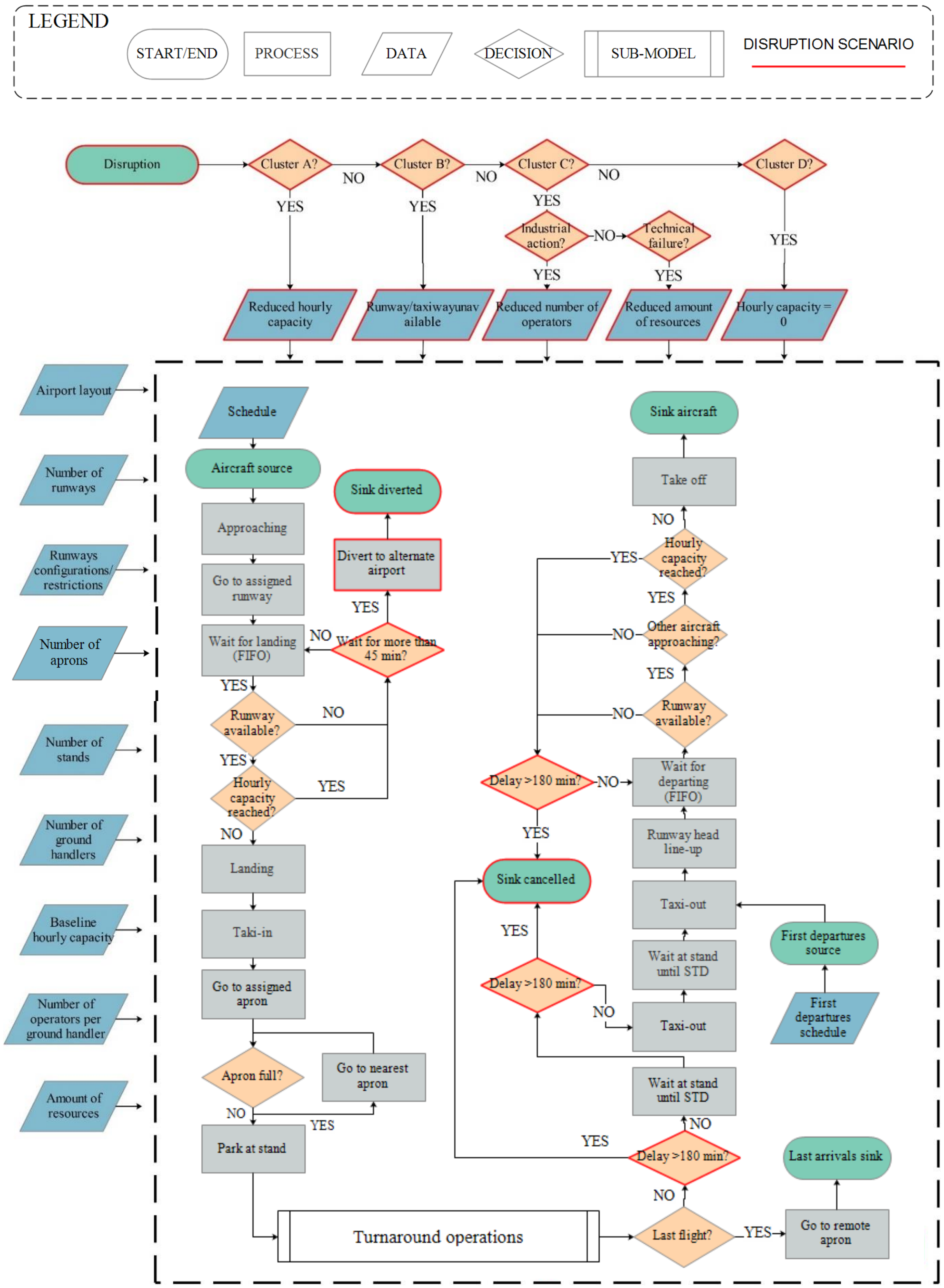


Figure 6.2. Architecture of the simulation model

6.7. Verification and validation

Once the model has been implemented, it was necessary to check the goodness of the model by checking that:

- the model is correctly implemented with respect to the conceptual model, i.e. that it matches specifications and assumptions made (verification);
- the simulation represents the real system with high accuracy (validation).

Verification is the process of determining that the implemented model accurately represents the developer's conceptual description and specifications, without any bugs. The model has been debugged and verified, following an iterative procedure, for finding and eliminating all the bugs due to translation from the conceptual model to the AnyLogic one. Specifically, model verification has been performed by checking:

- If the sequence of activities is consistent with actual airport operations;
- If activities effectively occur during the simulation period;
- In the disrupted scenarios, if results are logically consistent with actual performance under similar disruptions.

To support the verification stage, the animated version of the model enables the user to verify that the simulated activity is appropriate for the chosen scenario and to adjust resources and operating rules to produce an accurate level of real operations' representation. It illustrates the status of the airport at any point in the simulation time and shows movements of aircraft on the airfield.

Once verified, the model has been validated. The validation process consists of determining how much a model is an accurate representation of the real world, considering the perspective of the intended use of the model. The model has been validated by using the comprehensive set of event logs of simulated activity during the simulation period produced by the AnyLogic model. They provide statistics regarding arrivals, delays and turnaround times, hourly or during the entire simulation period. These logs are analysed to obtain simulation details and performance summaries at several dimensions.

Specifically, in order to validate the model, the *STD* was used to check the consistency between the simulated times and level of traffic, and to verify if everything happens exactly according to the schedule. Flight schedules, in terms of movements/hour, and arrivals and departures in the simulation model (output) were expected to match. Furthermore, in order to understand the extent to which the model reasonably depicts true operations, validation includes the following checks:

- If statistics for taxi-in, taxi-out and turnaround operations reflect real operations durations;
- In the disrupted scenarios, delay statistics are examined to see if they are consistent with historical data.

As a result, the conclusion was drawn that the model implementation represents with satisfactory accuracy the initial conceptual model (verification) and recreates the real system (validation).

7. APPLICATION AND RESULTS

7.1. Introduction

The methodology described in previous sections has been applied to four different disruptions, one for each of the clusters described in Chapter 4.

For each of the disruption, the following data are known:

- Duration of the disruption t_d (hours);
- Start hour (time of the day);
- For disruption belonging to clusters A and D, the reduction in capacity *RED* (see Section 5.3, Eq. 5.10);
- For the disruption of cluster B, the number of runways closed;
- For the disruption of cluster C, the percentage of operators on strike.

Moreover, for each case, the total delay of the disruption was known and retrieved from the Network Operation Reports published very year from EURCONTROL (EUROCONTROL 2017, 2018). The delay provided by EUROCONTROL was used as indicator to validate the disruption scenarios. The four disruptions scenarios are shown in Table 7.1.

For each of the disruption scenarios, a simulation model has been implemented by using AnyLogic, as described in Section 6, and validated by comparing simulations' output with real data. For the airports analysed, schedules were built by using data made available by the website Flightradar24 (https://www.flightradar24.com) and refer to the day of disruption (line 4 of Table 7.1), from 03:00 AM to midnight.

Each simulation model is run for a period T of 35 hours, from 03:00 AM to 13:00 of the successive day. Even if scheduled flights end at midnight, an additional time is considered to allow potential delayed flights to complete airside processes and take-off inside the simulation period.

Given the stochasticity of the model, multiple simulation runs are required in order to obtain accurate and reliable results. Then, for each of the simulation performed and described in the remaining of this Chapter, several replications have been carried out and model accuracy tested by determining the variability of turnaround time and departure delay. Results were considered valuable after 20 runs, obtaining an error lower than 5% for both quantities. In what follows, only average values will be reported.

Table 7.1. Disruptions used to validate the model

CLUSTER	A	B	C	D
Airport	Amsterdam Schiphol	Barcelona El Prat	Berlin Tegel	Hamburg
Airport Code (IATA/ICAO)	AMS/EHAM	BCN/LEBL	TEG/EDDT	HAM/EDDH
Disruption type	Radar issues	Aircraft on runway	Ground service industrial action	Power issues
Date	01/02/2017	14/08/2018	08/02/2017	03/06/2018
T_d (h)	7	2.5	6	3
Start	09:00 AM	12:00 AM	08:00 AM	10:00 AM
	RED = 60 %	1 RWY	$P_{m,d}$ = 40%	*RED* = 0 %
Delay	11,406	1,212	5,687	1,012

7.2. Cluster A: Amsterdam Schiphol Airport

7.2.1. Airport and disruption description

Amsterdam Airport Schiphol (AMS/EHAM), located 9 kilometres southwest of Amsterdam, is the main international airport of the Netherlands. It covers a total area of 6,887 acres (2,787 ha) of land and is the third busiest airport in Europe in terms of passenger volume and the second busiest in Europe in terms of aircraft movements (EUROCONTROL, 2018c). In 2018, Amsterdam Schiphol welcomed approximately 71.1 million passengers (up 3.7%) with 499,444 aircraft movements and more than 1.72 million tonnes of cargo. In 2018, Schiphol was able to offer a total of direct connections to 327 destinations in 98 countries, scheduled by 108 different airlines. (Schiphol Group, 2018).

AMS has six runways, one of which is used mainly by general aviation (3800 m., 3500 m., 3453 m., 3400 m., 3300 m., 2014 m. respectively). The airport is built as one large terminal (a single-terminal concept), with approximately 165 boarding gates including eighteen double jetway gates used for wide body aircraft (Schiphol Group, 2018). The airside area comprises 6 aprons with a total of 94 stands. The main characteristics of AMS are shown in Table 7.2, while the layout of the airport is shown in figure 7.1.

Table 7.2. Principal characteristics of AMS

Number of runways	Declared capacity[1]	Mov/year[2]	Average mov/day[3]	Aircraft stands[4]	Number of ground handlers[5]
5	102	499,444	1366	94	3

On 1st February 2017, malfunctioning radar systems led to dozens of flights cancelled and long delays. At around 9 AM (local time), "*EUROCONTROL warned of a "critical systems issue" affecting Amsterdam Schiphol airport, and told pilots to "expect delays/diversions". The fault apparently occurred with radar correlation software, which compares and assesses information from primary and secondary radar*" (www.independent.co.uk).

[1] Data retrieved from https://ext.eurocontrol.int/airport_corner_public/EDDC
[2] Data retrieved from https://ec.europa.eu/eurostat/statistics-explained/index.php/Air_transport_statistics
[3] Computed as the number of movements/year divided by 365
4 Data retrieved from https://www.routesonline.com/route-exchange/airports/
5 Data retrieved from https://www.businessairnews.com/hb_airports.html

Seven hours later, the fault was detected, and the disruption cleared, however EUROCONTROL reported that the system could remain unstable for the successive hours. EUROCONTROL estimated this disruptive event to have caused approximately 11,000 minutes of ATFM delays (Network Operations report, 2017, EUROCONTROL).

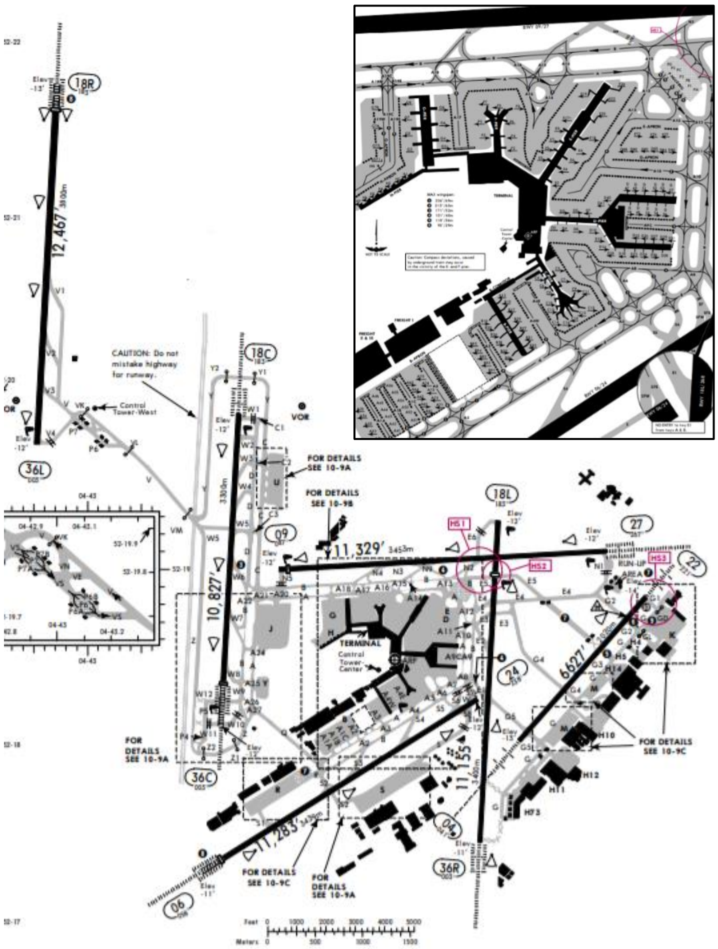


Figure 7.1. AMS airside layout, with detailed zoom of aprons. Source: ww1.jeppesen.com

7.2.2. Baseline scenario

The simulation refers to the disrupted day, precisely the 1st February 2017. During this day, 697 flights are scheduled to depart and 685 to land, with varied airlines and aircraft types - the fleet includes a mix of 20% wide body aircraft, with the remaining 80% of narrow-body ones.

A simulation is run for the base scenario, and results confirm that no significant delays occur in the absence of disruptions. Table 7.3. shows output in terms of total number of arrivals (N_{ARR}), departures (N_{DEP}) and the total number of movements (N_{TOT}) during the simulation period and results precisely match the daily schedule. Turnaround operations have an average duration of 42 minutes, with a minimum of 38 and a maximum of 51 minutes; these results are consistent with real operations and in line with previous studies (Schmidt 2017), where similar average turnaround times are obtained by analysing real data.

Table 7.3. Base scenario simulation's output

	N_{ARR}	N_{DEP}	N_{TOT}	$\overline{TAT}$ (min)	St. Dev. (min)
N° of flights	685	697	1382	42.12	2.31

The graph in Figure 7.2 shows aircraft arrivals (a) and departures (b) per hour during the simulation period (histogram in grey), in adherence with the real flight schedule (black line). From the graph it is evident that hourly aircraft movements (departures and arrival) occur in line with real ones. Figure 7.3. provides the scatter plot which compares the Scheduled Time of Arrival *STA* (horizontal axis) for each aircraft against the Actual Time of Arrival *ATA* (vertical axis) during the simulation. Similarly, figure 7.4. plots the Scheduled Time of Departure *STD* (x-axis) against the Actual Time od Departure in the simulation model (*ATD*, y-axis). By performing a simple linear regression, it results that, in both cases, data present very strong positive correlation and the value of the coefficient of determination R^2 is very high (0.999). Thus, outputs confirm the goodness of the model and its capability of correctly reproducing real systems. In terms of arrivals, it is possible to notice two peak periods, between 07:00 and 09:00 in the morning and between 18:00 and 20:00 in the afternoon, with more than 60 movements per hour. Regarding departures, a higher number of departures occur between 08:00 and 10:00 in the morning, from 12:00 and 14:00 and from 20:00 to 21:00.

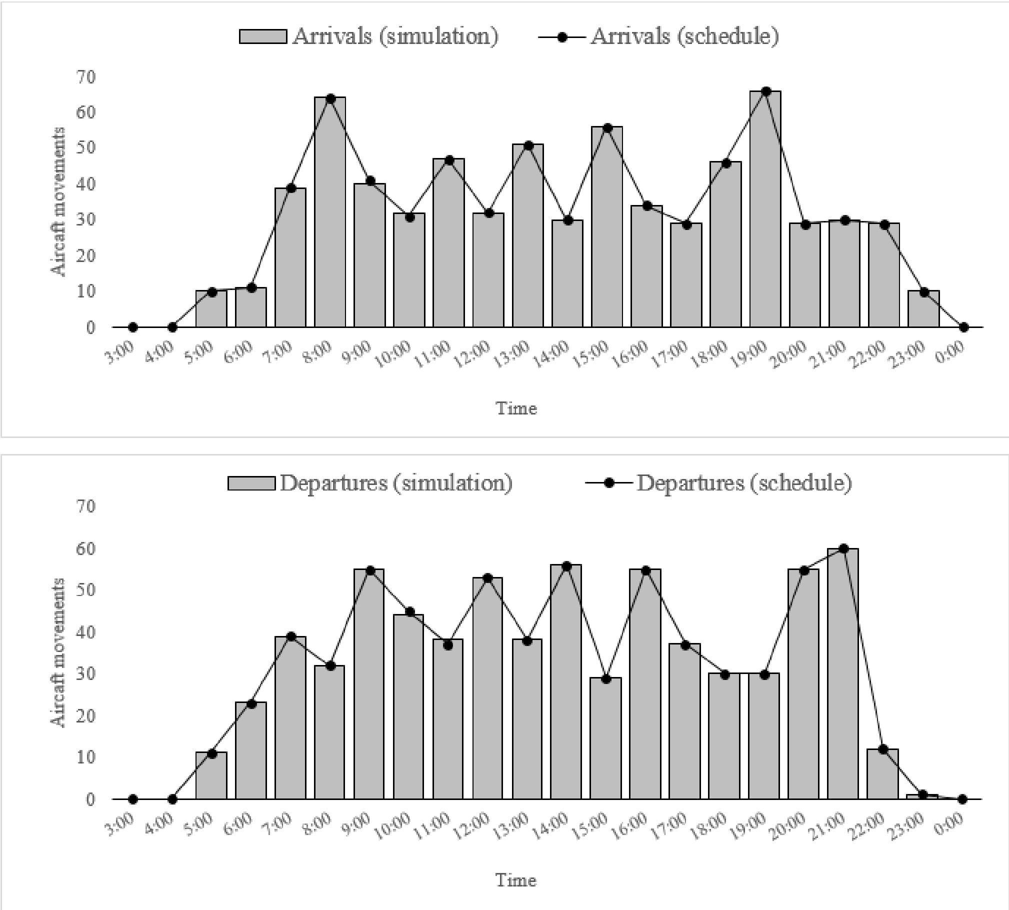


Figure 7.2. (a) arrivals and (b) departures per hour in the baseline scenario

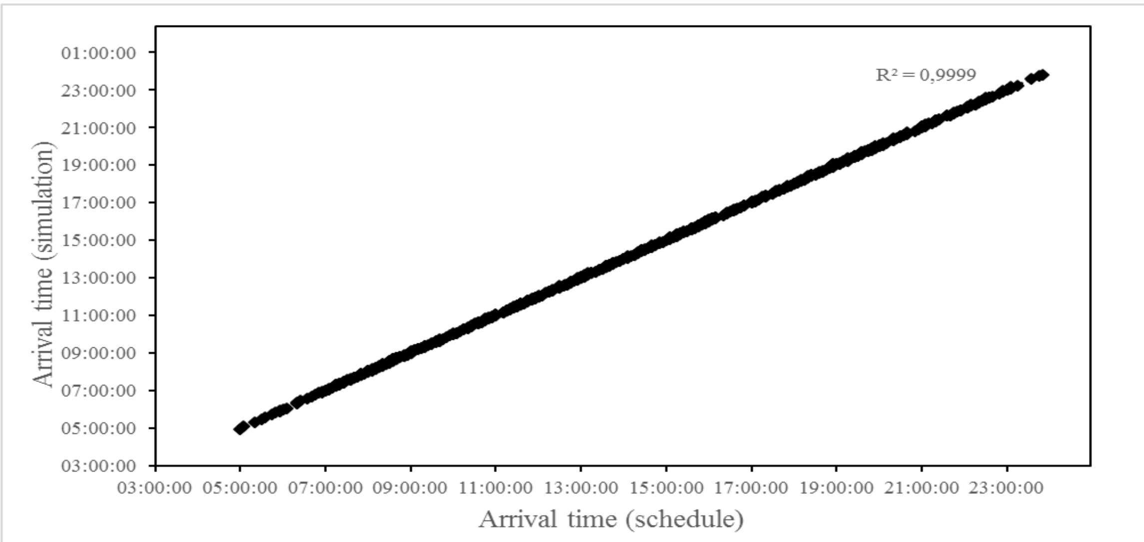


Figure 7.3. Scatterplot of STA (schedule) and ATA (simulations' output) in the base scenario

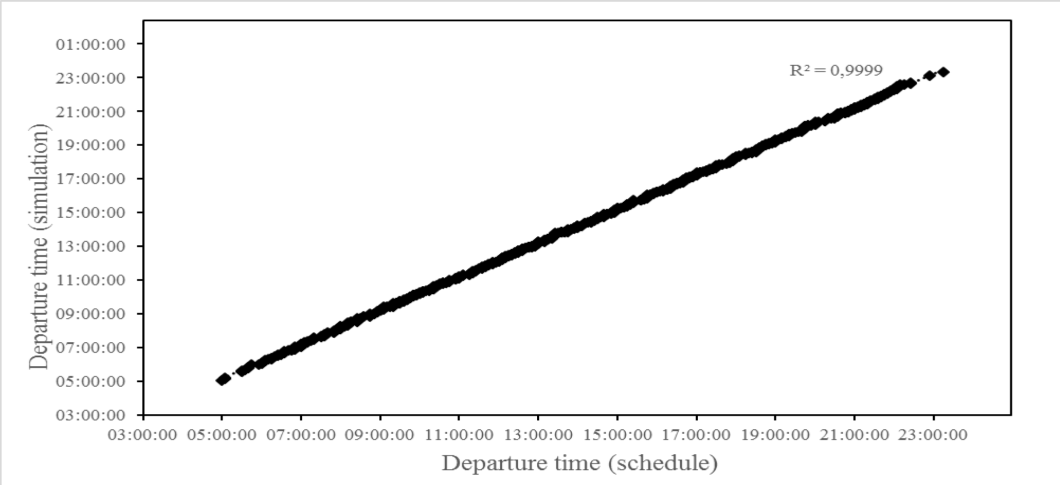


Figure 7.4. Scatterplot of STD (schedule) and ATD (simulations' output) in the base scenario

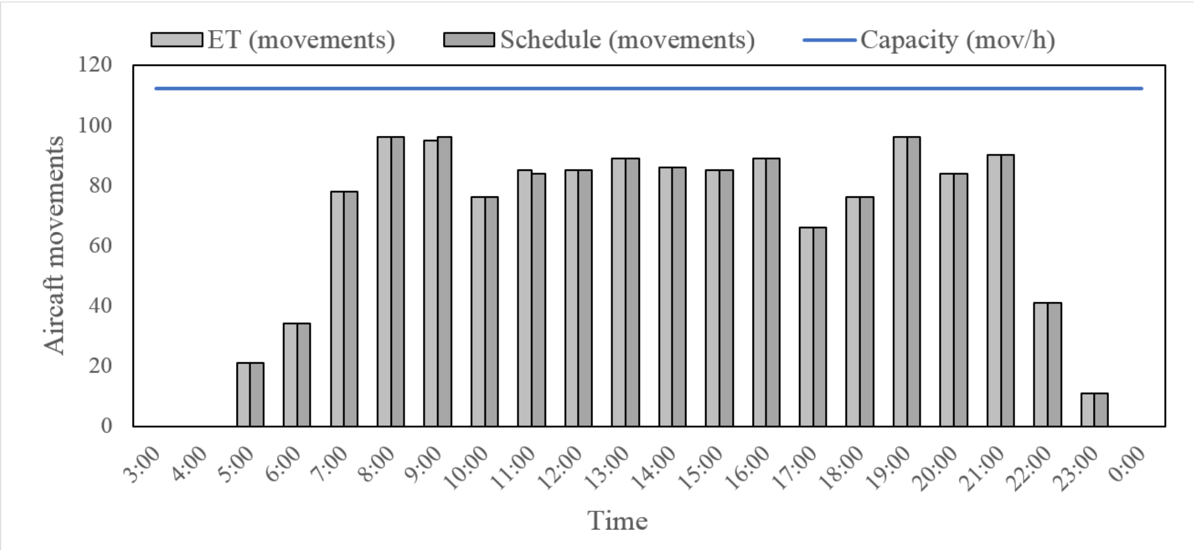


Figure 7.5. Effective throughput Rate during the simulation period

In the baseline scenario, as expected, no flight is departing late. The histogram in figure 7.5 shows the Effective Throughput $ET_{A,t}$ for the entire simulation period, where $ET_{A,t}$ has been computed in accordance with Eq. 5.8:

$$ET_{A,t} = \sum_{t=1\ hour} n_{DEP} + n_{ARR} \left[\frac{movements}{hour}\right] \qquad \text{(Eq. 7.1)}$$

The periods of maximum throughput are from 08:00 and 09:00 AM and between 19:00 and 20:00 in the afternoon, with around 90 movements/hour. However, these values are amply lower than the capacity of the airport *CAP*, equal to 112 movements/hour and shown in blue in the figure below. The Average Throughput Rate ATR_A during the period of analysis is equal to:

$$ATR_A = \frac{\sum_T ETR_{A,t}}{T} = 65\% \qquad \text{(Eq. 7.2)}$$

7.2.3. Disrupted scenario

In the disrupted scenario, radar problems caused a reduction of in the arrival and departure capacity. The simulation is run considering a disruption with a duration T_d = 7 hours, from 09:00 in the morning to 16:00 in the afternoon. Airport capacity in the disrupted scenario becomes:

$$CAP_{A,D} = CAP_A * (1 - RED) = 112 * 0.4 = 45\ movements/hour \qquad \text{(Eq. 7.3)}$$

Thus, from the beginning of the disruption, delays occur and several flights arrive and depart late with respect to their schedule (see table 7.4). In particular, 31 flights depart late and 31 are diverted to alterative aerodromes (out of the simulation) and the total impact in terms of movements is equal to:

$$TI = N_L + N_D + N_C = 162\ flights \qquad \text{(Eq. 7.4)}$$

The total departure delay obtained during the simulation period is equal to 10,813.00 minutes, with an average of 82 minutes approximately. This value is closely comparable to the delay information registered by EUROCONTROL (11,060 minutes, see Table 7.1), with a slight variation of only 2%. This result confirms the validity of the model and its capability of correctly reproducing the disrupted scenario.

Table 7.4. Disrupted scenario simulation's output

	Total	**Average**	**St. Dev.**
Departure delay (min)	10,813.00	82.72	23.47
Arrival delay (min)	815.71	31.37	6.43
Turnaround time (min)	-	42.15	1.94

Impacted flights	
N_L	131
N_C	0
N_D	31

In terms of turnaround, no significant increase has been experienced by the system; in fact, the disruption causes a reduction in the landing and take-off capacity, and do not influence ground operations. The *Turnaround Loss TL* is then equal to 0:

$$TL = \frac{\overline{TAT}_D\ (m|J_{mP}) - \overline{TAT}\ (m|J_{mP})}{\overline{TAT}\ (m|J_{mP})} = 0\% \qquad \text{(Eq. 7.5)}$$

Figure 7.6 illustrates the delay per hour of simulation (in grey). As long as the disruption progresses (in red in figure), delays increase because of accumulated congestion during airside operations and the maximum delay is reached at the end of the disruption (16:00). The accumulated departure delay during the simulation period *T* is shown in red in figure 7.7; in the same graph, bars indicate the hourly departure delay. When the disruption is cleared, systems' performance requires an extra time to return at the reference level, where no delays occur. In fact, the presence of several flights with inherited reactionary lateness, accumulated during the disruption period, causes the airport system to need ad additional time (recovery time, in pink in figure) to return to the initial performance. Operations return fully functional at 19:00, 3 hours after the end of the disruption. The total duration of the disruption is then equal to:

$$t_t = t_d + t_r = 7 + 3 = 10\ hours \qquad \text{(Eq. 7.6)}$$

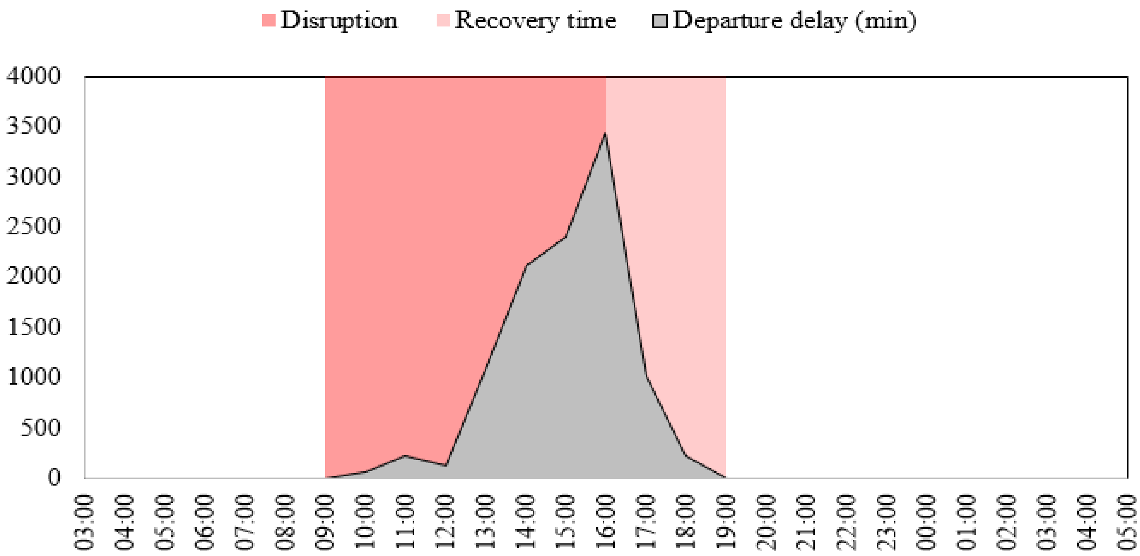


Figure 7.6. Departure delay (in grey)

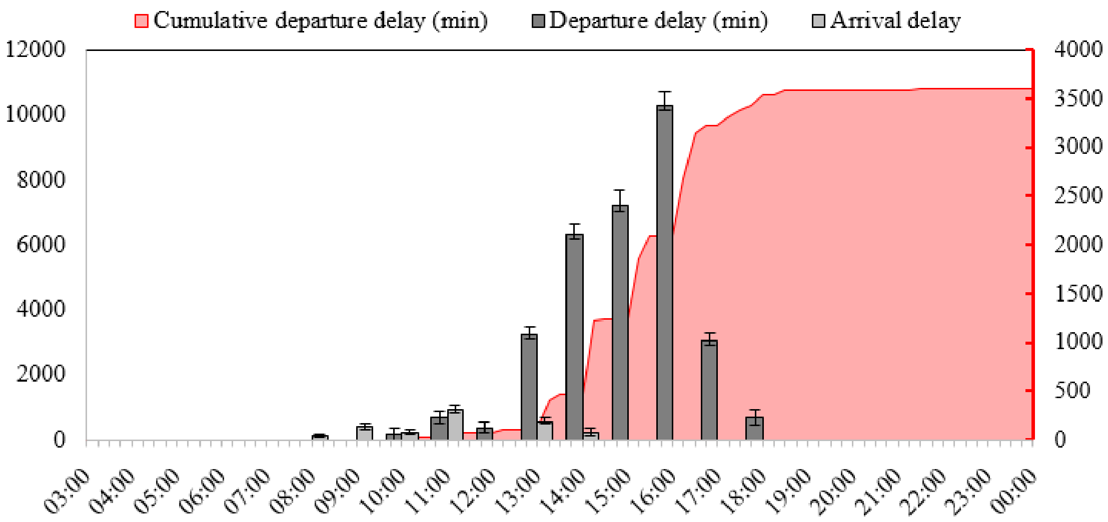


Figure 7.7. Cumulative departure delay

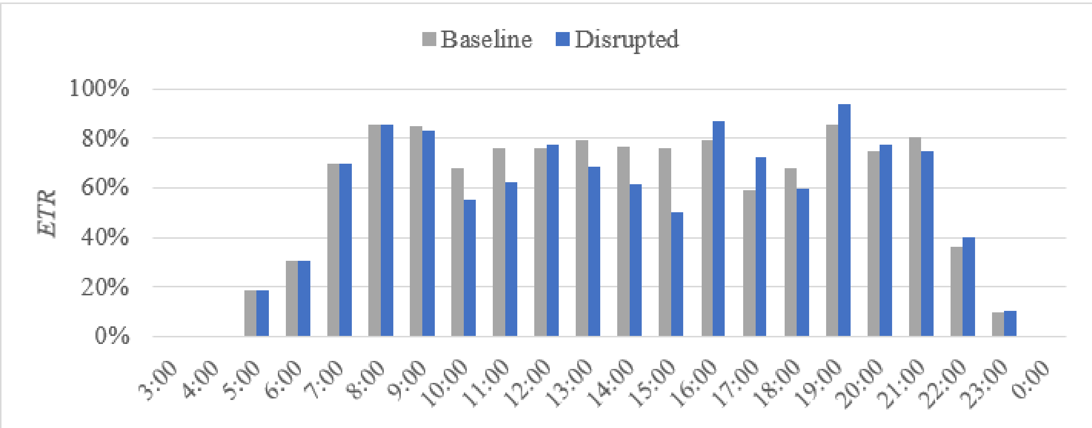


Figure 7.8. Effective Throughput Rate

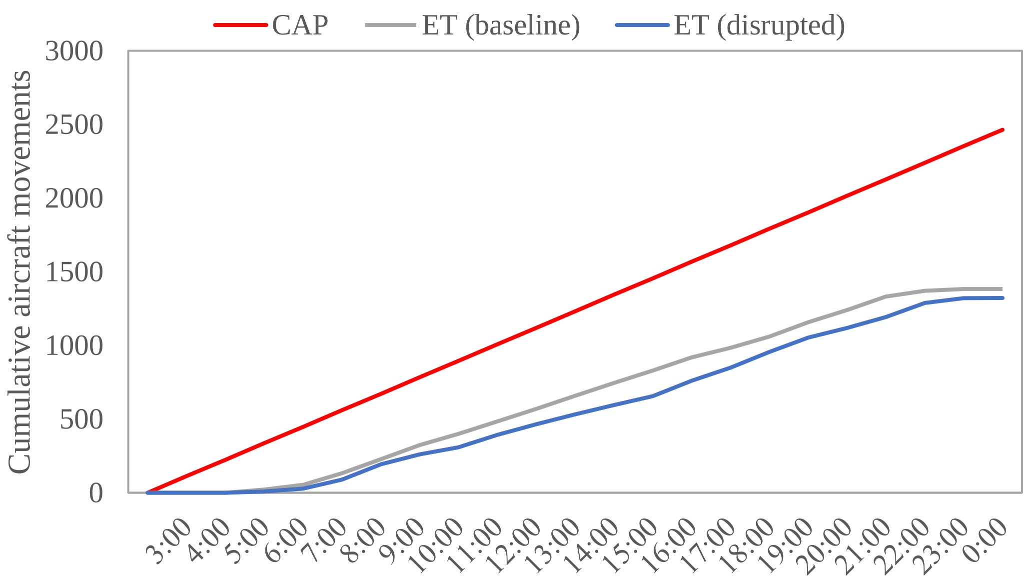


Figure 7.9. Cumulative Effective Throughput Rate

The graph in figure 7.8 depicts the cumulative Effective Throughput Rate through the entire day of analysis in both the baseline (grey) and disrupted scenarios (blue). The figure below shows the same indicator, but on an hourly basis. In both graphs, it is evident a loss of capacity starting from the beginning of the disruption (09:00) and propagating for the rest of the day.

Then, the Capacity Loss *CL* is evaluated as the difference between the baseline Average Throughput Rate ATR_A and the disrupted Average Throughput Rate $ATR_{A,D}$ during the entire disruption period:

$$CL = ATR_A(t_t) - ATR_{A,D}(t_t) = \frac{\sum_{tt} ETR_{A,t}}{t_t} - \frac{\sum_{tt} ETR_{A,D,t}}{t_t} = 0.77 - 0.66 = 0.11 = 11\% \quad \text{(Eq. 7.7)}$$

While previous results allow to comprehend the impacts of the disruption during the day from a broader perspective, resilience and vulnerability indicators are evaluated in order to obtain synthetic measures of the consequences of the disruptive event and compare them with other scenarios. Vulnerability is then evaluated according to Eq. 5.32:

$$V_{A,D} = \beta_L N_L + \beta_D N_D + \beta_C N_C = 0.47 * 131 + 0.42 * 31 + 1 * 0 = 75\ flights \quad \text{(Eq. 7.8)}$$

Were weights β_i are evaluated with respect to the cost of a cancelled flight $COST_C$ (see Chapter 4):

$$\beta_L = \frac{COST_L}{COST_C} = \frac{100 * \overline{DEL}_{DEP}}{17{,}650} = 0.47$$

$$\beta_D = \frac{COST_D}{COST_C} = \frac{7{,}400}{17{,}650} = 0.42$$

$$\beta_C = \frac{COST_C}{COST_C} = 1$$

The resilience is then evaluated as the difference between the baseline and disrupted Average Throughout Rate, both referred to the deviation time:

$$RES = \frac{CL}{t_t} = \frac{ATR_A(t_t)}{t_t} - \frac{ATR_{A,D}(t_t)}{t_t} * 100 = \frac{0.11}{10} * 100 = 1.1 \quad \text{(Eq. 7.9)}$$

7.3. Cluster B: Barcelona-El Prat Airport

7.3.1. *Airport and disruption description*

Barcelona-El Prat Josep Tarradellas Airport (BCN/LEBL), also known as El Prat Airport, is an international airport located 12 km from the centre of Barcelona, in Spain. It is the second largest and busiest airport in Spain, and the seventh busiest in Europe. In 2018, El Prat Airport handled more than 50 million passengers, with a growth of 6.1% with respect to previous year. Most of the traffic is domestic, and intercontinental connections have not generated a significant amount of traffic during the last year. The airport has 3 runways in service, two parallel (07L/25R and 07R/25L), and a cross runway 02/20.

Table 7.5. BCN airport characteristics

Number of runways	Declared capacity[1]	Mov/year[2]	Average mov/day[3]	Aircraft stands[4]	Number of ground handlers[5]
3	64	310,250	850	170	4

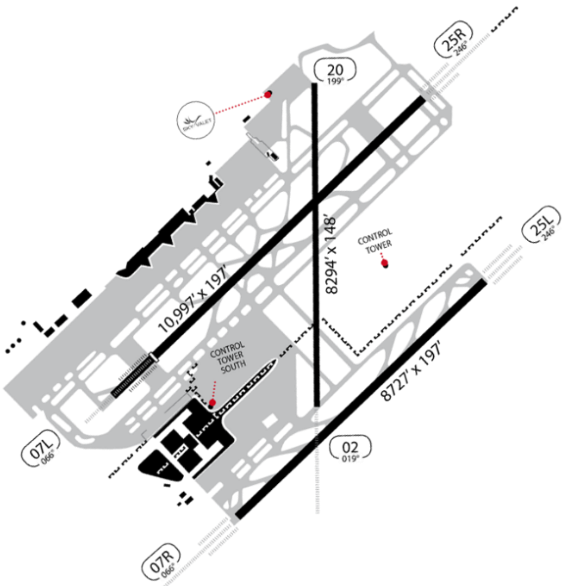


Figure 7.10. BCN layout

[1] Data retrieved from https://ext.eurocontrol.int/airport_corner_public/EDDC
[2] Data retrieved from https://ec.europa.eu/eurostat/statistics-explained/index.php/Air_transport_statistics
[3] Computed as the number of movements/year divided by 365
4 Data retrieved from https://www.routesonline.com/route-exchange/airports/
5 Data retrieved from https://www.businessairnews.com/hb_airports.html

On August 14, 2018, A Rossiya Boeing 747-40 from Moscow, around noon, landed on Barcelona's runway 25R with about 500 people on board. It rolled out safely but was subsequently unable to vacate the runway due to a nose wheel steering fault. The aircraft stopped on the runway; the runway returned available almost 2 hours after landing.

7.3.2. *Baseline scenario*

The simulation is run referring to the disrupted day, i.e. precisely the 14th August 2018. During this day, 493 flights are scheduled to land at the airport and 516 to depart. The fleet includes a mix of 90% narrow body aircraft, with the remaining 10% of wide body ones.

A simulation is run for the base scenario, and the output from the simulation prove that no significant delays occur in the reference scenario and no flight is departing late. The total number of arrivals (N_{ARR}), departures (N_{DEP}) and the total number of movements (N_{TOT}) during the simulation period match precisely the daily schedule, as shown in Table 7.6. Turnaround operations have an average duration of 42 minutes, as in the case of Amsterdam Airport: these results are consistent with real operations.

Table 7.6. Base scenario output

	N_{ARR}	N_{DEP}	N_{TOT}	$\overline{TAT}$ (min)	St. Dev. (min)
N° of flights	493	516	1009	42.72	2.31

Figure 7.11 provides the scatter plot which compares the *STA* (horizontal axis) for each aircraft against the *ATA* (vertical axis) during the simulation. Similarly, figure 7.12 plots the *STD* (x-axis) against the in the simulation model (*ATD*, y-axis). In both cases, data present very strong positive correlation and the value of the coefficient of determination R^2 is very high (0.9999 and 0.9996 respectively). Also in this case, outputs confirm the goodness of the model and its capability of correctly reproducing real systems.

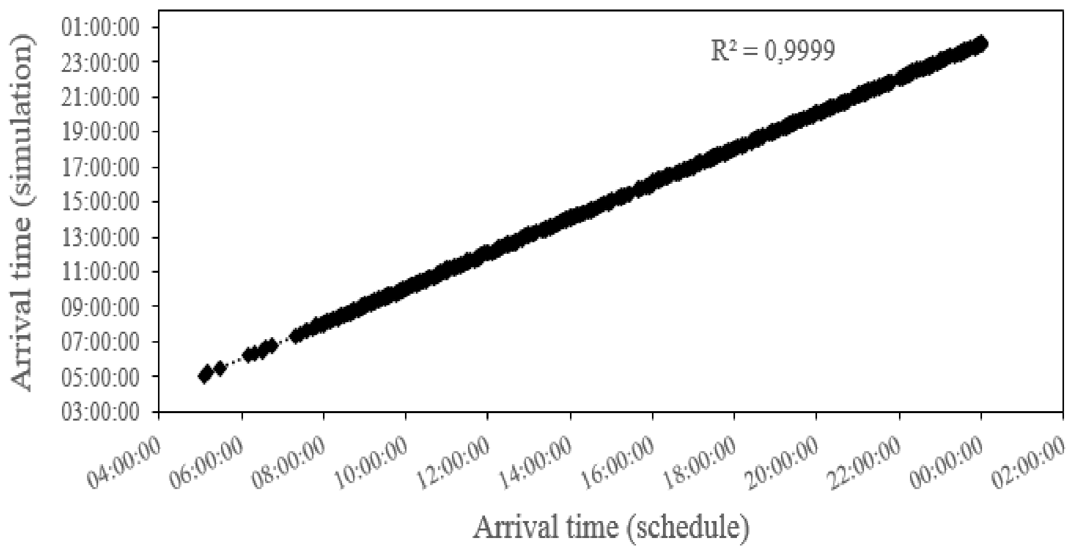


Figure 7.11. Scatter plot of STA against ATA

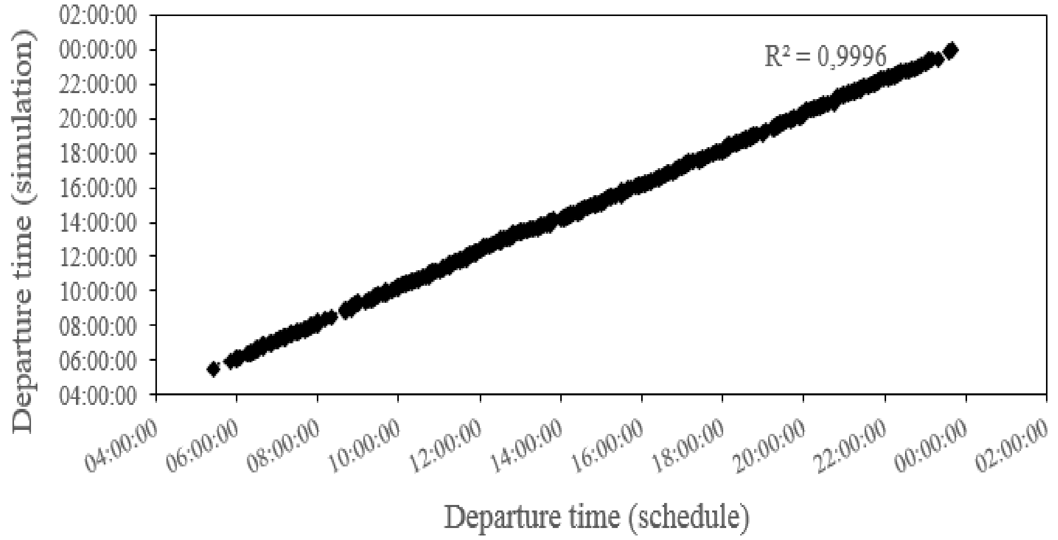
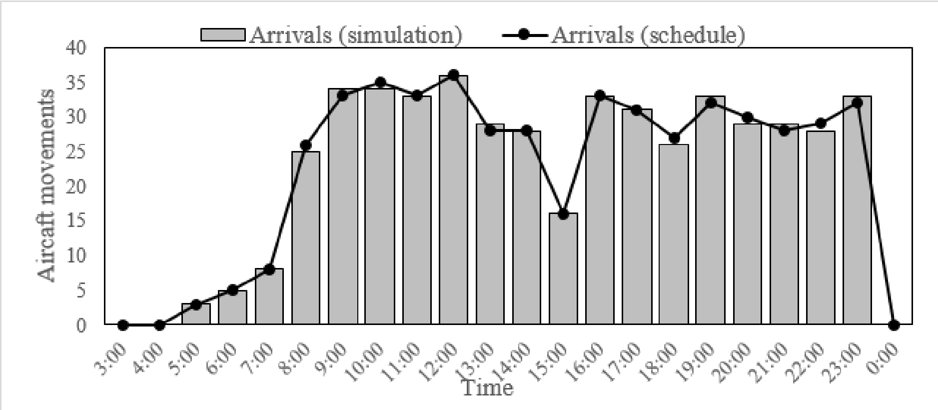


Figure 7.12. Scatter plot of STD against ATD



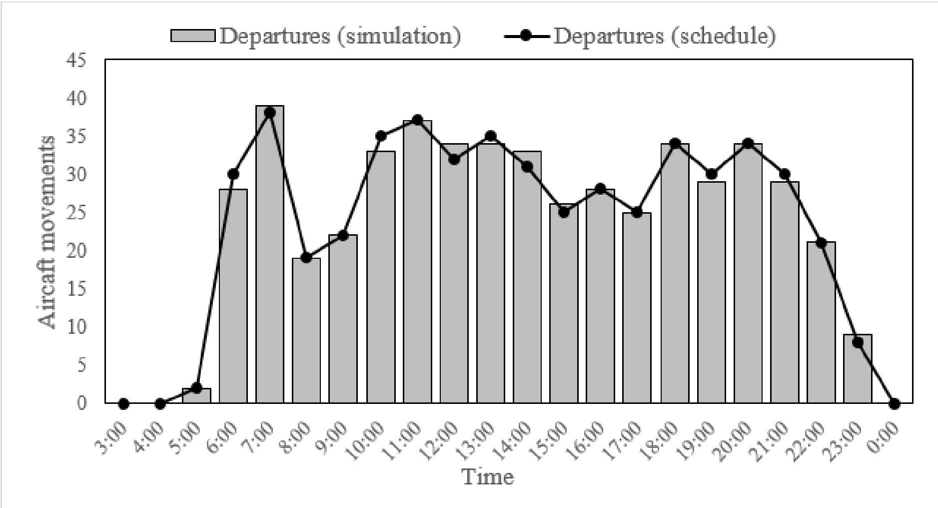


Figure 7.13. Aircraft (a) arrivals and (b) departures

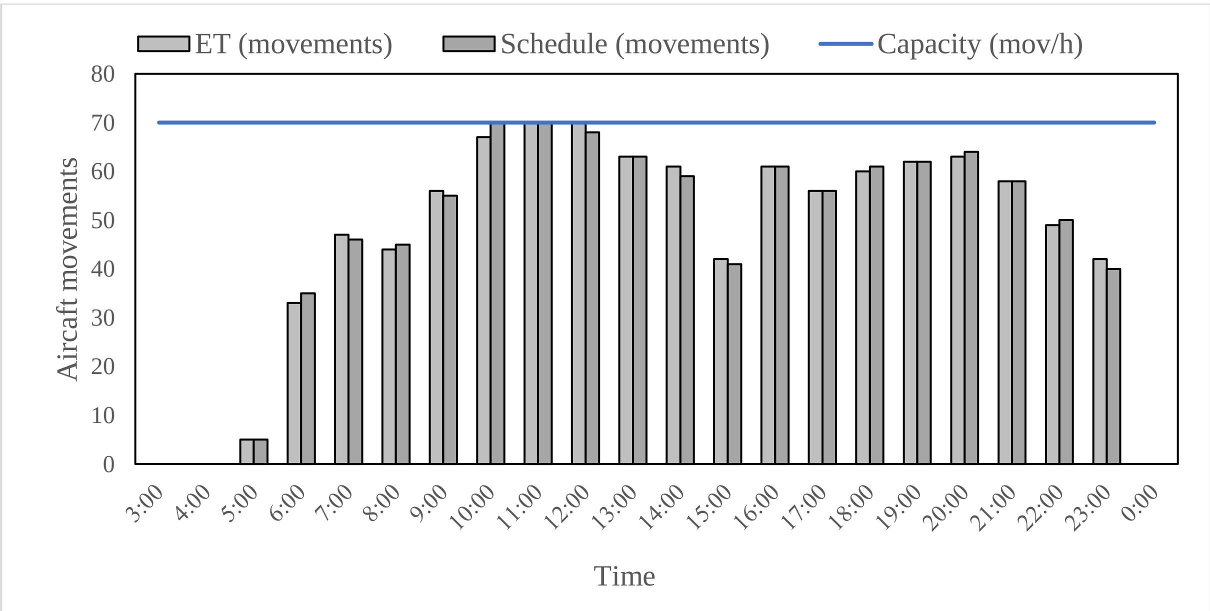


Figure 7.14. Effective Throughput Rate during the simulation period

The graph in Figure 7.13 shows aircraft arrivals (a) and departures (b) per hour during the simulation period (histogram in grey), in adherence with the real flight schedule (black line). Regarding arrivals, the peak period is from 10:00 to 12:00, with a maximum of 38 landing aircraft. In terms of departures, the maximum number of aircraft is observed at 07:00 in the morning. The period of maximum throughput (figure 7.14) is between 10:00 and 12:00 in the morning, when it reaches 70 movements/hour. This value matches exactly the capacity of the airport *CAP*, equal to 70 movements/hour and shown in blue in the figure; it reasonable to assume that, in these periods, the infrastructure is used at almost its capacity and the most undesirable criticalities are expected.

The Average Throughput Rate ATR_A during the period of analysis is equal to:

$$ATR_A = \frac{\sum_T ETR_{A,t}}{T} = 76\% \qquad \text{(Eq. 7.10)}$$

7.3.3. Disrupted scenario

In the disrupted scenario, one of the runways of the airport is unavailable because of an incident. Thus, arriving and departing aircraft have to use the remaining two runways. The simulation is run considering a disruption with a duration t_d = 2.5 hours, from 12:00 in the morning to 14:30 in the afternoon.

From the beginning of the disruption, delays occur and some flights arrive and depart late with respect to their schedule, as shown in figure, which illustrates the delay per hour of simulation (in grey). As long as the disruption progresses (in red in figure 7.15), delays increase because of accumulated congested airside operations and a maximum delay of 1,212 minutes is experienced during the last hour of the disruption (15:00 - 16:00). The accumulated departure delay during the simulation period *T* is shown in red in figure 7.16; in the same graph, bars indicate the hourly departure delay.

When the disruption is cleared, systems' performance requires an extra time to work off handle the accumulated congestion and return at the reference level, where no delays occur. A recovery time t_r of 2.5 is necessary to make the operations return fully functional and the system is recovered at 18:00. The total duration of the disruption is then equal to:

$$t_t = t_d + t_r = 2.5 + 2.5 = 5\ hours \qquad \text{(Eq. 7.11)}$$

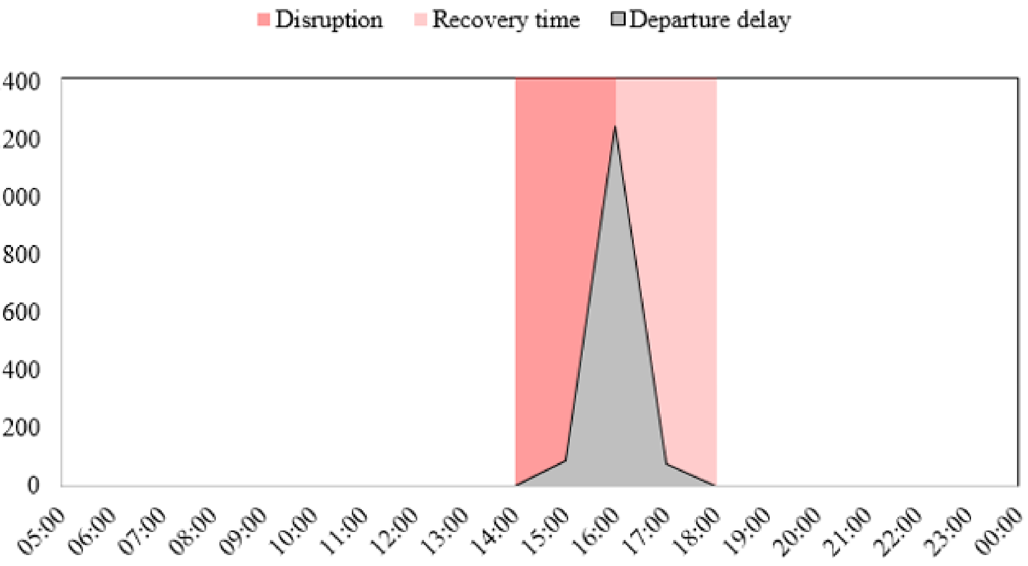


Figure 7.15. Departure delay (in grey)

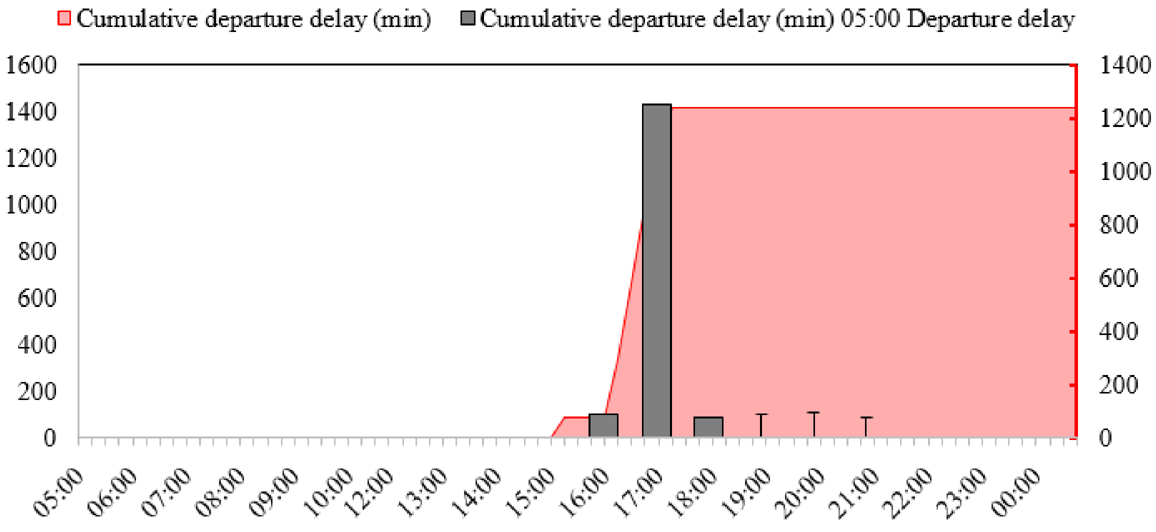


Figure 7.16. Cumulative departure delay

Table 7.7. Disrupted scenario output

	Total	Average	St. Dev.
Departure delay (min)	1,412	83.09	33.32
Arrival delay (min)	64.49	16.12	5.94
Turnaround time (min)	-	42.45	2.19

Impacted flights	
N_L	17
N_C	0
N_D	0

The total delay experience results to be equal to 1,412 minutes, with an average of 83 minutes per flight. The total delay obtained from the simulation is 15% higher with respect to the one registered by EUROCONTROL (1,212 minutes, see Table 7.7), which can be considered a good approximation. During the entire disrupted period, 17 flights are delayed and forced to depart late (see table). In this case, the total impact is given by the late departures only:

$$TI = N_L + N_D + N_C = 17\ flights \qquad \text{(Eq. 7.12)}$$

The total departure delay obtained during the simulation period is equal to 10,813.00 minutes, with an average of 82 minutes approximately. This value is closely comparable to the delay information registered by EUROCONTROL (11,060 minutes, see Table 7.1), with a slight variation of only 2%. This result confirms the validity of the model and its capability of correctly reproducing the disrupted scenario.

Also in this case, turnaround operations are not affected by the disruption, and the turnaround time remains the same as in the baseline scenario. The Turnaround Loss TL is then equal to 0:

$$TL = \frac{\overline{TAT}_D\ (m|J_{mP}) - \overline{TAT}\ (m|J_{mP})}{\overline{TAT}\ (m|J_{mP})} = 0\% \qquad \text{(Eq. 7.13)}$$

The graph in figure 7.17 shows the cumulative Effective Throughput Rate through the entire day of analysis in both the baseline (grey) and disrupted scenarios (blue). The figure below displays the same indicator, but on an hourly basis. In both graphs, a loss of capacity can be observed from the beginning of the disruption (12:00) and propagating for the successive four hours (until 16:00).

Then, the Capacity Loss *CL* is evaluated as the difference between the baseline Average Throughput Rate ATR_A and the disrupted Average Throughput Rate ATR_D during the entire simulation period:

$$\begin{aligned} CL = ATR_A(t_t) - ATR_{A,D}(t_t) = \frac{\sum_{tt} ETR_{A,t}}{t_t} - \frac{\sum_{tt} ETR_{A,D,t}}{t_t} = 0.85 - 0.73 \\ = 0.12 = 12\% \end{aligned} \qquad \text{(Eq. 7.14)}$$

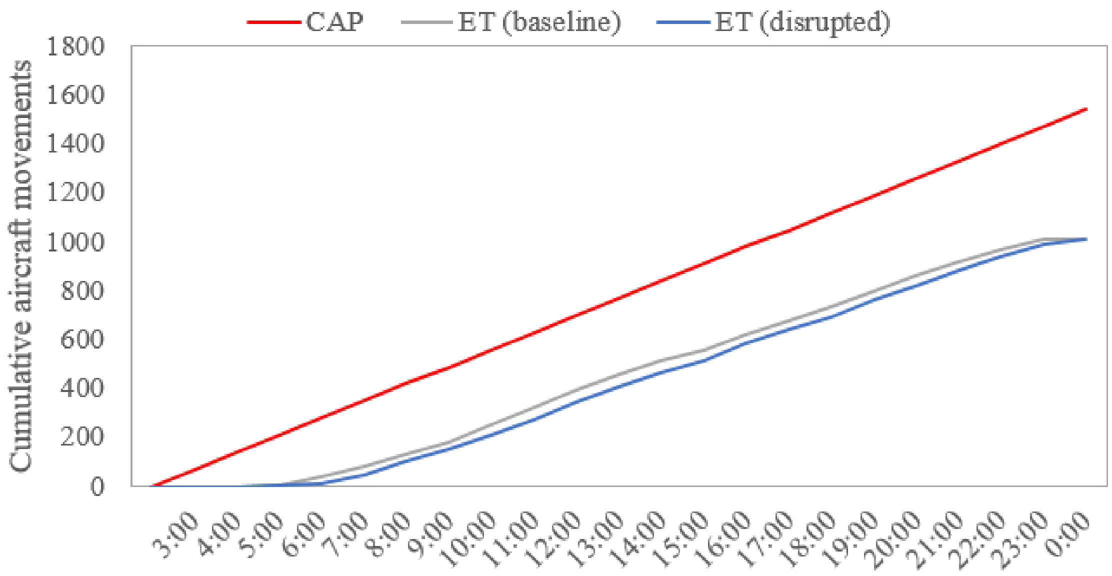


Figure 7.17. Cumulative Effective Throughput Rate

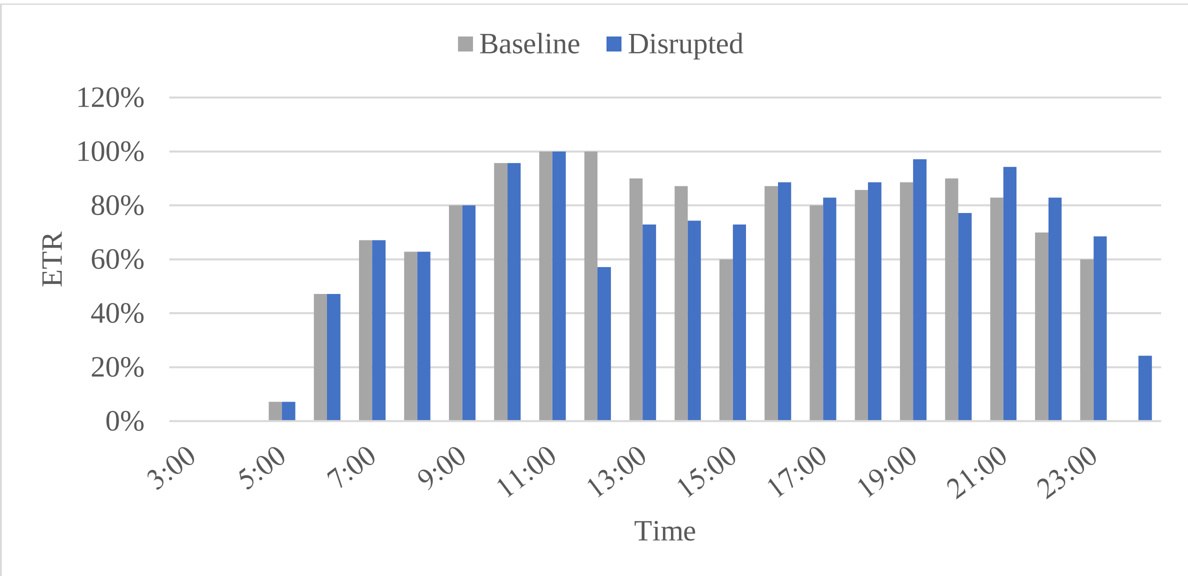


Figure 7.18. Effective Throughput Rate

As before, vulnerability and resilience indicators are computed to obtain synthetic measures of the consequences of the disruption. Vulnerability is then evaluated according to Eq. 5.32:

$$V_{A,D} = \beta_L N_L + \beta_D N_D + \beta_C N_C = 0.47 * 17 + 0.42 * 0 + 1 * 0 = 8\ flights \qquad \text{(Eq. 7.15)}$$

Were weights β_i are evaluated with respect to the cost of a cancelled flight *COST*$_C$ (see Chapter 4):

$$\beta_L = \frac{COST_L}{COST_C} = \frac{100 * \overline{DEL}_{DEP}}{17{,}650} = 0.47$$

$$\beta_D = \frac{COST_D}{COST_C} = \frac{7{,}400}{17{,}650} = 0.42$$

$$\beta_C = \frac{COST_C}{COST_C} = 1$$

The resilience is then evaluated as the difference between the baseline and disrupted Average Throughout Rate, both referred to the deviation time:

$$RES = \frac{CL}{t_t} = \frac{ATR_A(t_t)}{t_t} - \frac{ATR_{A,D}(t_t)}{t_t} * 100 = \frac{0.12}{5} * 100 = 2.4 \qquad \text{(Eq. 7.16)}$$

7.4. Cluster C: Tegel airport

7.4.1. Airport and disruption description

Tegel airport (TXL/EDDT) is the main airport in Berlin, Germany. Located 8 km north-west from Berlin, it is currently the fourth busiest airport in Germany, with more than 20 million passengers handled in 201 and 22 million in 2018. It serves several European destinations and some intercontinental routes.

It has two parallel runways (08L/26R and 08R/26L) with a length of 3,023 and 2,428 meters respectively. Runway 08L/26R is usually used for landings and wide-body aircraft take-offs, while runway 08R/26L is the main departure runway for narrow-body aircraft. A general night flight prohibition applies from 23:00 until 06:00. The airport building consists of 5 terminals, which share the same building. The main features of the airport are shown in Table 7.6.

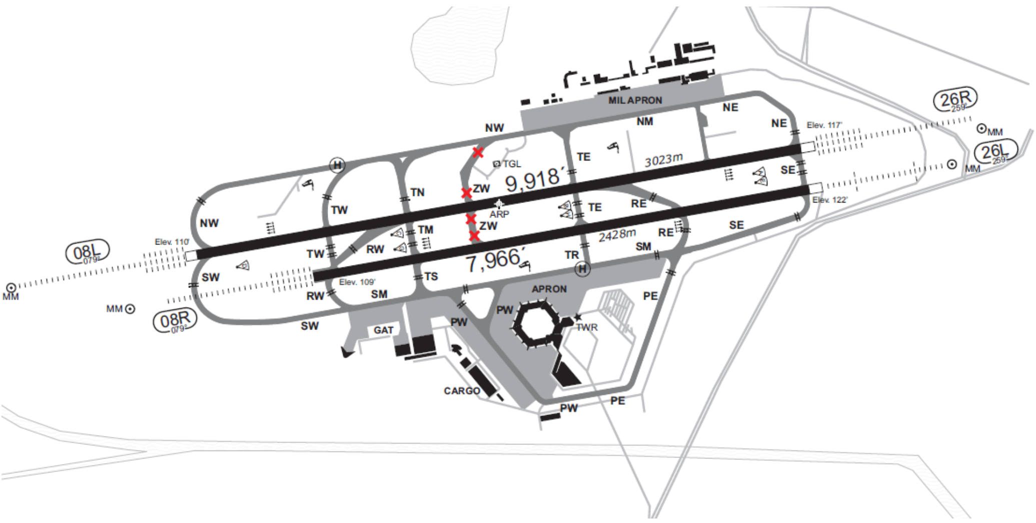


Figure 7.19. TXL layout

Table 7.8. TXL characteristics

Number of runways	Declared capacity[1]	Mov/year[2]	Average mov/day[3]	Aircraft stands[4]	Number of ground handlers[5]
2	52	167,900	460	50	1

[1] Data retrieved from https://ext.eurocontrol.int/airport_corner_public/EDDC
[2] Data retrieved from https://ec.europa.eu/eurostat/statistics-explained/index.php/Air_transport_statistics
[3] Computed as the number of movements/year divided by 365
4 Data retrieved from https://www.routesonline.com/route-exchange/airports/
5 Data retrieved from https://www.businessairnews.com/hb_airports.html

On 8th February 2017, an industrial action of ground operators caused serious delays and plethora of cancellations of scheduled flights*: "The walkout by staff of Berlin Tegel and Schoenfeld were to last from 8 AM local time (07:00 UTC) to around 14:00 on Wednesday, trade union Verdi said. Around 2000 ground staff-including those dealing with flight check-ins and baggage handling – were to take part in the strike, it added. Others involved in six-hour walkout were flights marshals and plane refuelling crews"* (www.dw.com).

At the end of the industrial action, delays continued throughout the day reaching a total of 5,687 minutes of ATFM delays (Network Operations report, 2017, EUROCONTROL).

7.4.2. Baseline scenario

The simulation refers to the 8th February 2017, which is the day in which the industrial action takes place. During this day, his day, 260 flights are scheduled to depart and 262 to land (with a total of 522 movements), with different airlines and aircraft types. The fleet mix is constituted mainly by narrow body aircraft (98%), with only a 2% of wide body ones.

After running the simulation for the base scenario, results show that no significant delays occur in the absence of disruptions, and all flights are departing on time. Table 7.19 shows output in terms of total number of arrivals (N_{ARR}), departures (N_{DEP}) and the total number of movements (N_{TOT}) during the simulation period and results precisely match the daily schedule. Also in this case turnaround operations have an average duration of 42 minutes, with a maximum of 50 and a minimum of 39 minutes; these results are consistent with real operations and in line with previous studies (Schmidt, 2017).

Table 7.9. Base scenario outputs

	N_{ARR}	N_{DEP}	N_{TOT}	$\overline{TAT}$ (min)	St. Dev. (min)
N° of flights	262	260	522	42.17	1.74

The graph in Figure 7.10 shows aircraft arrivals (a) and departures (b) per hour during the simulation period (histogram in grey), compared to real flight schedule (black line). From the graph it is evident that hourly aircraft movements (departures and arrival) adhere to real data. Figure 7.11. provides the scatter plot which compares the *STA* (horizontal axis) for each aircraft against the *ATA* (vertical axis) during the simulation. Similarly, figure 7.12. plots the Scheduled

Time of Departure *STD* (x-axis) against the Actual Time od Departure in the simulation model (*ATD*, y-axis). These two graphs show that, in both cases, there is a very strong correlation between simulation daily output and real schedule (R^2 = 0.9999 for arrivals, R^2 = 0.9998 for departures). Thus, outputs confirm the goodness of fit of the model and its capability of correctly reproducing real systems.

In terms of arrivals, the majority of departures occur from late afternoon to the end of the day, precisely at 16:00 and between 18:00 and 22:00. Regarding departures, during the morning the most part of flights is scheduled between 06:00 and 09:00, while in the afternoon a peak period is visible between 17:00 and 19:00 and at 21:00.

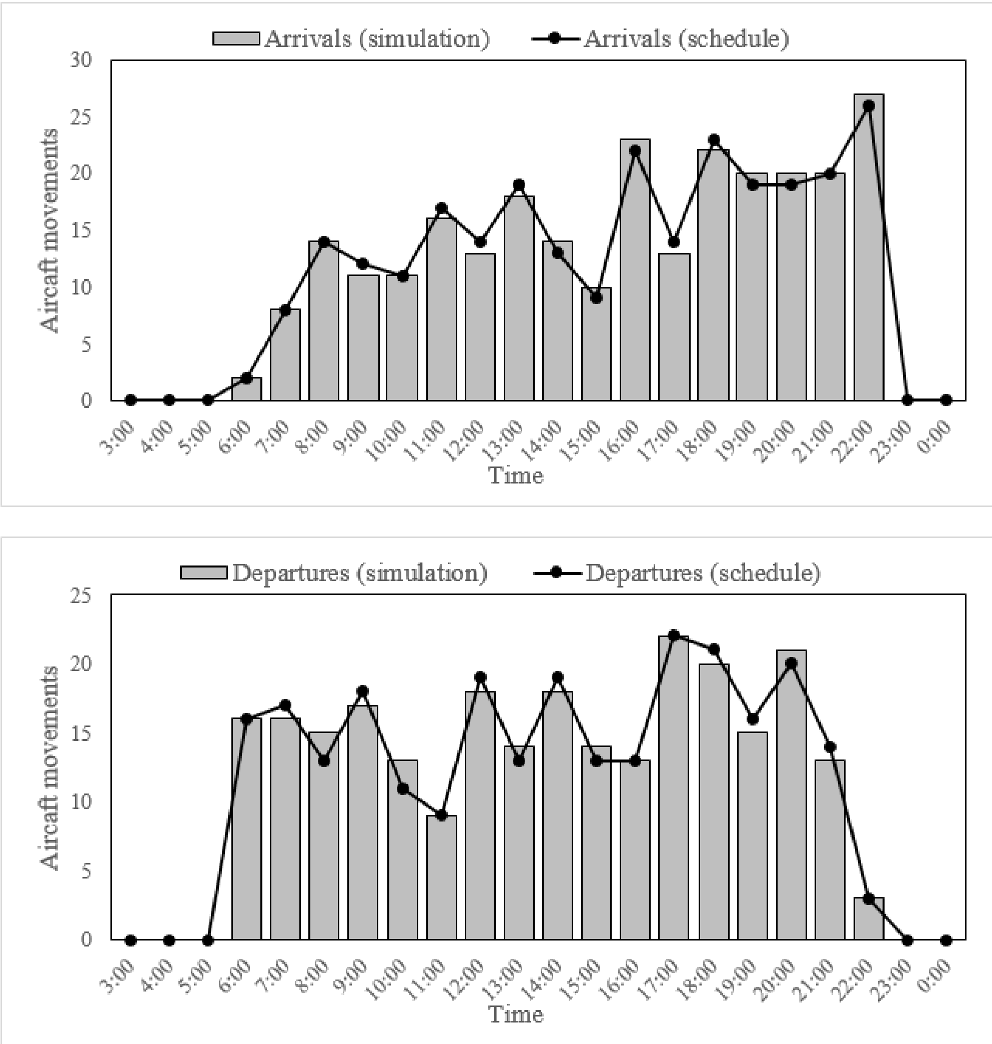


Figure 7.20. Aircraft arrivals (a) and departures (b) during the simulation period T

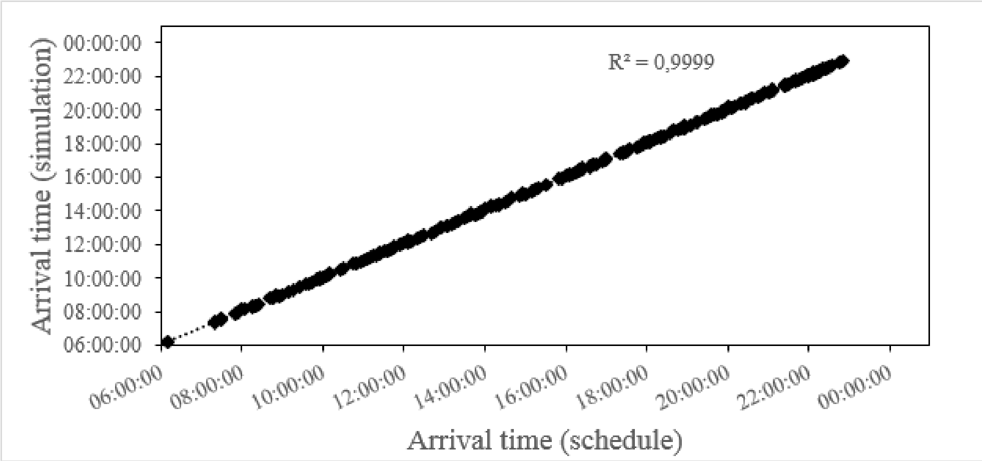


Figure 7.21. STA against ATA

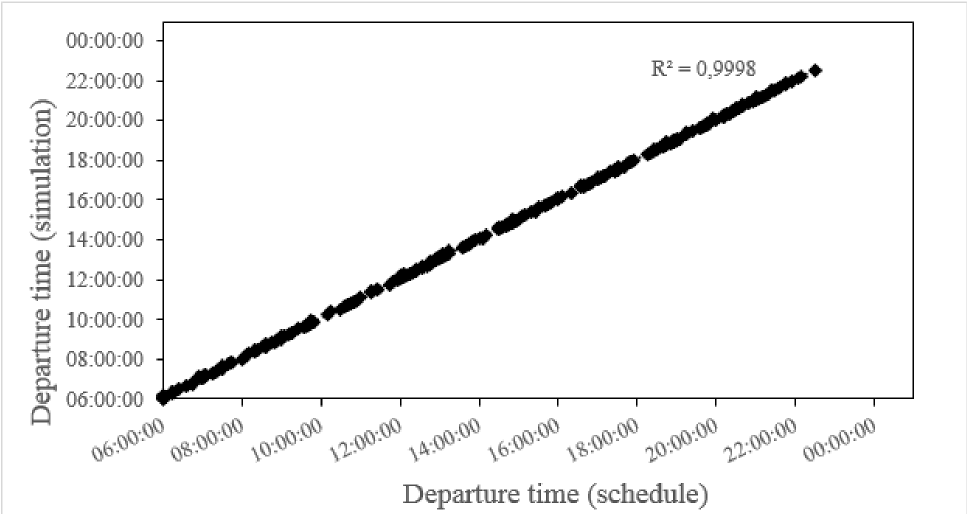


Figure 7.22. STD against ATD

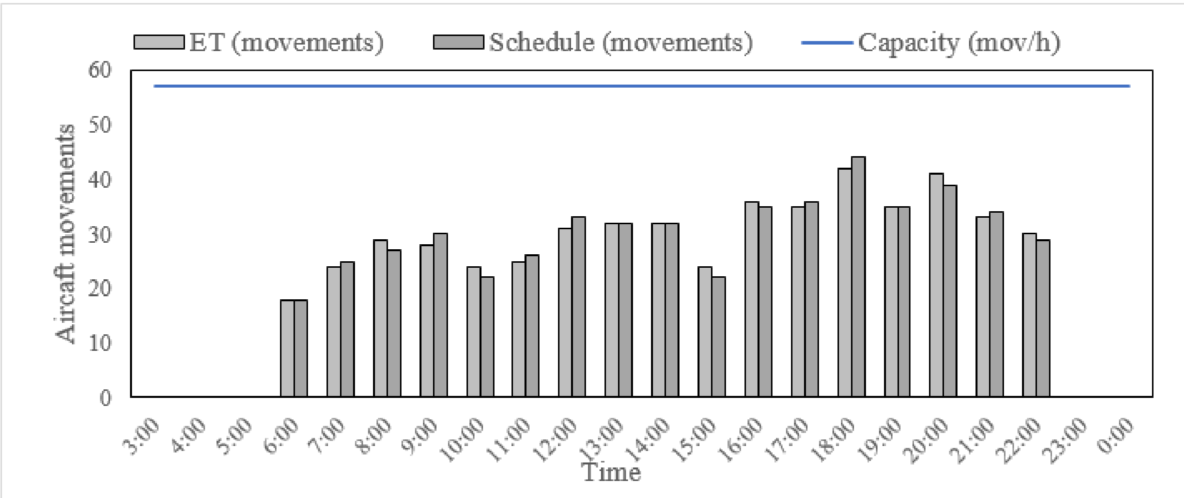


Figure 7.23. Effective Throughput Rate

The periods of maximum throughput are from 08:00 and 09:00 AM and between 19:00 and 20:00 in the afternoon, with around 90 movements/hour. However, these values are far below the capacity of the airport *CAP*, equal to 57 movements/hour and shown in blue in figure 7.23. The Average Throughput Rate ATR_A during the period of analysis is equal to:

$$ATR_A = \frac{\sum_T ETR_{A,t}}{T} = 54\% \qquad \text{(Eq.7.17)}$$

7.4.3. Disrupted scenario

In the disrupted scenario, an industrial action of grand handler operators is simulated with a duration t_d = 8 hours, from 08:00 in the morning to 14:00 in the afternoon. of available operators J_m is reduced of a certain percentage $P_{m,d}$ and the number of available operators becomes:

$$J_{m,d} = J_m * (1 - 0.4) \qquad \text{(Eq.7.18)}$$

As a consequence, turnaround time increases and delays occur. Several flights depart late with respect to their schedule (see table 7.10). In particular, 50 flights depart late and 65 are diverted to alterative aerodromes (out of the simulation) and the total impact in terms of movements is equal to:

$$TI = N_L + N_D + N_C = 115\ flights \qquad \text{(Eq.7.19)}$$

In this scenario, there is no significative arrival delay; in fact, industrial actions affect operations principally at the ground level, causing delays in departures more than arrivals. The total departure delay obtained during the simulation period is equal to 5,517.00 minutes, with an average of approximately 110 minutes. This value is closely comparable to the delay information registered by EUROCONTROL (5,687 minutes, see Table 7.1), with a slight variation of only 2%. This result confirms the validity of the model and its ability of correctly reproducing the disrupted scenario.

In terms of turnaround, a significant increase can be observed during the industrial actions. In fact, in this case the most affected processes are the ones related to turnaround operations. It is evident from the graph in figure 7.25, where the turnaround time throughout the simulation period is shown. Specifically, the average turnaround time, which was equal to 42 minutes in the base scenario, more than doubles in the disrupted one, reaching the value of 89 minutes.

The Turnaround Loss *TL* is then equal to 0:

$$TL = \frac{\overline{TAT}_D\ (m|J_{mP}) - \overline{TAT}\ (m|J_{mP})}{\overline{TAT}\ (m|J_{mP})} = 112\% \qquad \text{(Eq.7.20)}$$

Table 7.10. Disrupted scenario outputs

	Total	Average	St. Dev.
Departure delay (min)	5,517.01	110.34	53.96
Arrival delay (min)	24.39	12.19	0.25
Turnaround time (min)	-	89.79	72.99

Impacted flights	
N_L	50
N_C	65
N_D	0

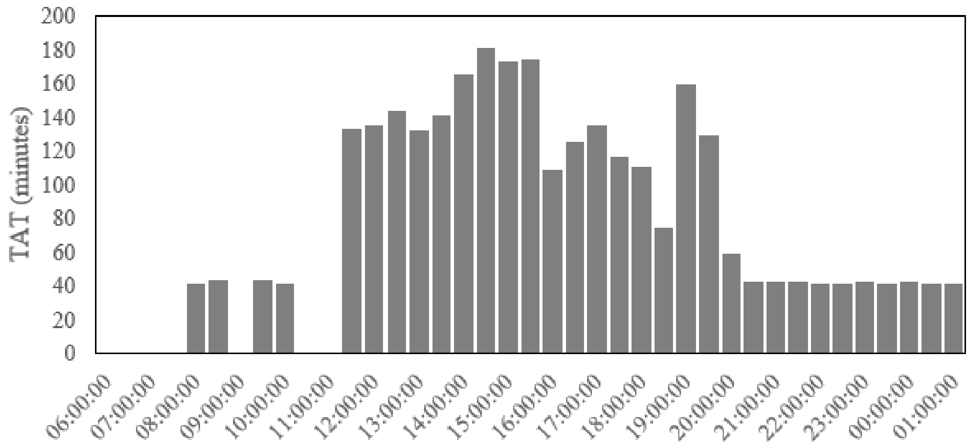


Figure 7.24. Hourly average turnaround time

Figure 7.26 below illustrates the delay per hour of simulation (in grey). From the beginning of the simulation, delays accumulate and propagate until the end of the day. The accumulated departure delay during the simulation period *T* is shown in red in figure 7.27. Even after the end of the industrial action (in red in figure) disruptions consequences last for a considerable amount of time. Operations return fully functional at 22:00, with a recovery time tr of 8 hours (in pink in figure). The total duration of the disruption is then equal to:

$$t_t = t_d + t_r = 6 + 8 = 14\ hours \qquad \text{(Eq.7.21)}$$

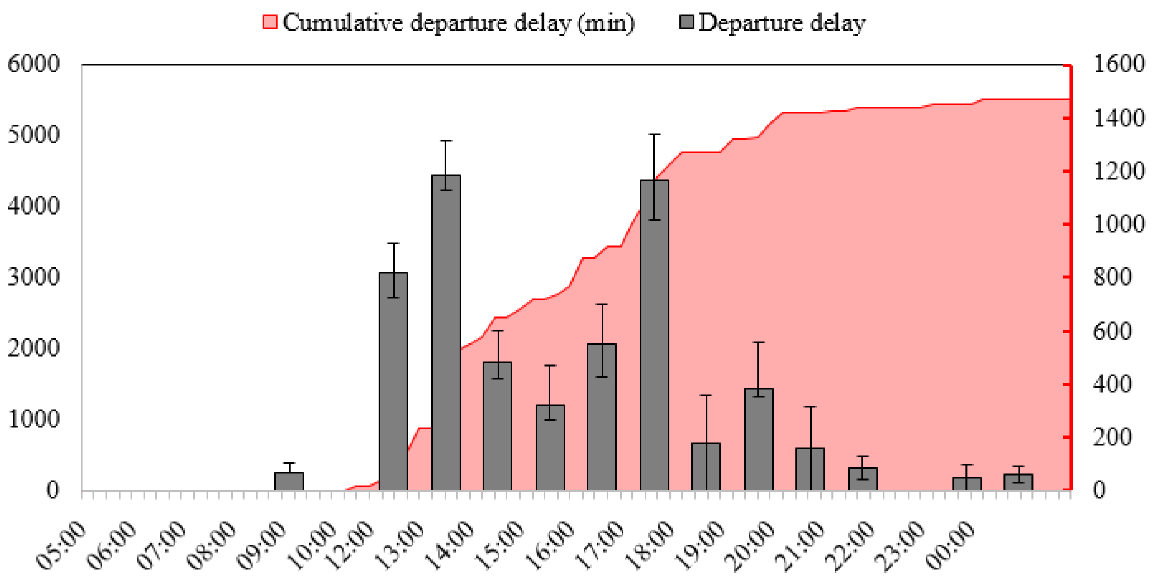


Figure 7.25. Cumulative departure delay

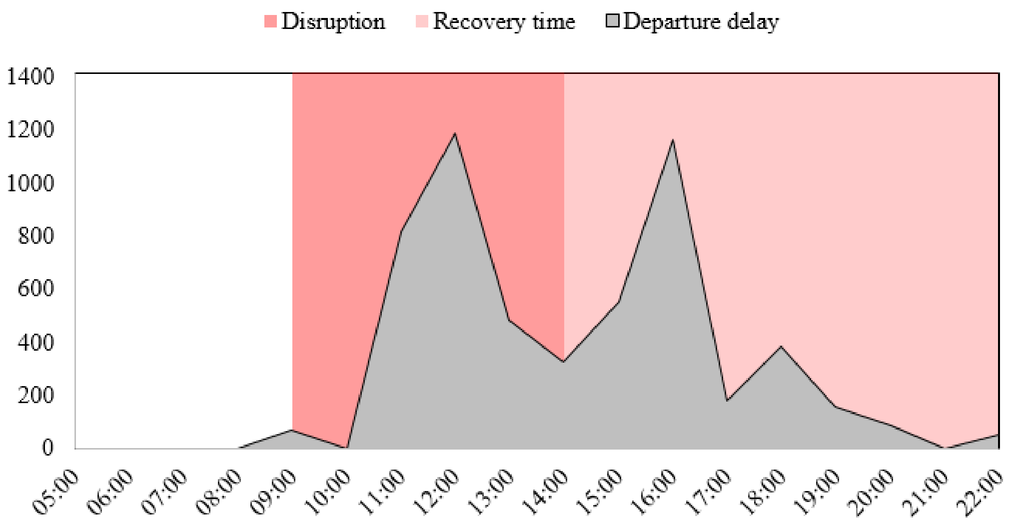


Figure 7.26. Departure delay

The graph in figure 7.28 depicts the cumulative Effective Throughput Rate through the entire day of analysis in both the baseline (grey) and disrupted scenarios (blue). It is evident a loss of capacity from the beginning of the disruption (09:00) and propagating for the rest of the day.

The Capacity Loss CL during the total disruption period is evaluated as the difference between the baseline Average Throughput Rate ATR_A and the disrupted Average Throughput Rate ATR_D during the total disruption period:

$$CL = ATR_{A,D}(t_t) - ATR_A(t_t) == 0.56 - 0.48 = 0.08 = 8\% \qquad \text{(Eq.7.22)}$$

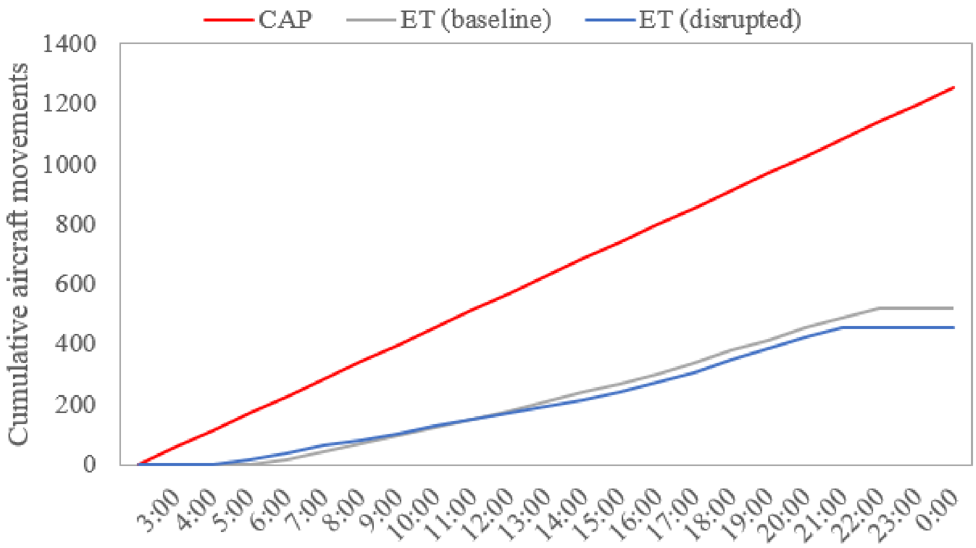


Figure 7.27. Cumulative Effective Throughput Rate

As before, vulnerability and resilience indicators are computed to obtain synthetic measures of the consequences of the disruption. Vulnerability is then evaluated according to Eq. 5.32:

$$V_{A,D} = \beta_L N_L + \beta_D N_D + \beta_C N_C = 0.63 * 50 + 0.42 * 0 + 1 * 65 = 97\ flights \qquad \text{(Eq.7.23)}$$

Were weights β_i are evaluated with respect to the cost of a cancelled flight $COST_C$ (see Chapter 4):

$$\beta_L = \frac{COST_L}{COST_C} = \frac{100 * \overline{DEL}_{DEP}}{17{,}650} = 0.63$$

$$\beta_D = \frac{COST_D}{COST_C} = \frac{7{,}400}{17{,}650} = 0.42$$

$$\beta_C = \frac{COST_C}{COST_C} = 1$$

The resilience is then evaluated as the difference between the baseline and disrupted Average Throughout Rate, both referred to the deviation time:

$$RES = \frac{CL}{t_t} = \frac{ATR_A(t_t)}{t_t} - \frac{ATR_{A,D}(t_t)}{t_t} * 100 = \frac{0.08}{14} * 100 = 0.57 \qquad \text{(Eq.7.24)}$$

7.5. Cluster D: Hamburg airport

7.5.1. Airport and disruption description

Hamburg airport (HAM/EDDH) is the international airport of Hamburg, the second-largest city in Germany. It is located 8.5 km north of the city centre and is the fifth-busiest of Germany's commercial airports in terms of handled passengers. In 2018, it counted more than 17 million passengers and approximately 150 thousand aircraft movements. In 2017, if featured flights to more than 130 European destinations and 3 long-haul routes.

The runway system is composed on two crossing runways (05/23 and 15/33), with a length of respectively 3,250 and 3,666 meters. The main apron 320,000 m_2 and features 54 aircraft parking stands. The principal attributes of the airport are show in Table 6.3.

Table 7.11. HAM characteristics

Number of runways	Declared capacity[1]	Mov/year[2]	Average mov/day[3]	Aircraft stands[4]	Number of ground handlers[5]
2	49	146,000	400	54	3

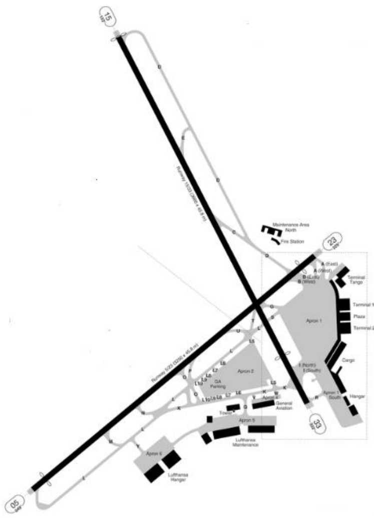


Figure 7.28. HAM layout

[1] Data retrieved from https://ext.eurocontrol.int/airport_corner_public/EDDC
[2] Data retrieved from https://ec.europa.eu/eurostat/statistics-explained/index.php/Air_transport_statistics
[3] Computed as the number of movements/year divided by 365
4 Data retrieved from https://www.routesonline.com/route-exchange/airports/
5 Data retrieved from https://www.businessairnews.com/hb_airports.html

On 3rd June 2018, a power issue caused the temporary complete closure of the airport, downing the capacity to zero: "*A sudden power failure crippled Hamburg Airport on Sunday, forcing the cancellation of scores of flights and stranding thousands of travellers. Operations ceased when the blackout hit the airport in the northern German port city around 10 AM (08:00 GTM). (…). The source of the power failure had been identified as an electrical short*" (www.dailysabah.com). Three hours later, the issue was solved, and the airport returned operative again. EUROCONTROL estimated this disruptive event to have caused 1,212 minutes of ATFM delays (Network Operations report, 2017, EUROCONTROL).

7.5.2. Baseline scenario

The simulation's schedule refers to the disrupted day, i.e. the 3rd June 2018. During this day, 188 flights are scheduled to depart and 191 to land (a total of 379 aircraft movements), with varied airlines and aircraft types. The fleet mix is composed primarily of narrow body aircraft (98%) with the remaining 2% of wide-body ones.

Running the simulation for the base scenario, results confirm that no significant delays occur in the absence of disruptions. Table 7.30. shows output in terms of total number of arrivals (N_{ARR}), departures (N_{DEP}) and the total number of movements (N_{TOT}) during the simulation period, which precisely match the daily schedule. Turnaround operations have an average duration of 43 minutes, with a minimum of 37 and a maximum of 50 minutes.

Table 7.12. Base scenario output

	N_{ARR}	N_{DEP}	N_{TOT}	$\overline{TAT}$ (min)	St. Dev. (min)
N° of flights	191	188	379	42.65	2.30

The graph in Figure 7.31 shows aircraft arrivals (a) and departures (b) per hour during the simulation period (histogram in grey), in adherence with the real flight schedule (black line). From the graph it is evident that hourly aircraft movements (departures and arrival) occur in line with real ones. In terms of arrivals, it is possible to notice the majority of aircraft land in the late afternoon, with a peak between 18:00 and 19:00 and another between 21:00 and 22:00. Regarding departures, two peak periods can be identified: in the morning, between 06:00 and 07:00, and I the afternoon, from 18:00 to 20:00.

Again, to verify the compliance between simulations' output and the real schedule, figure 7.32 and 7.33 provides, respectively: (i) the scatter plot which compares the *STA* (horizontal axis) for each aircraft against the *ATA* (vertical axis) during the simulation; (ii) the plot of the *STD* (x-axis) against the *ATD* in the simulation model (y-axis). In both cases, data present very strong positive correlation and the value of the coefficient of determination R^2 is very high (0.9999 for arrivals and 0.9996 for departures). Thus, outputs confirm the goodness of fitness of the model and its ability of correctly reproducing real systems.

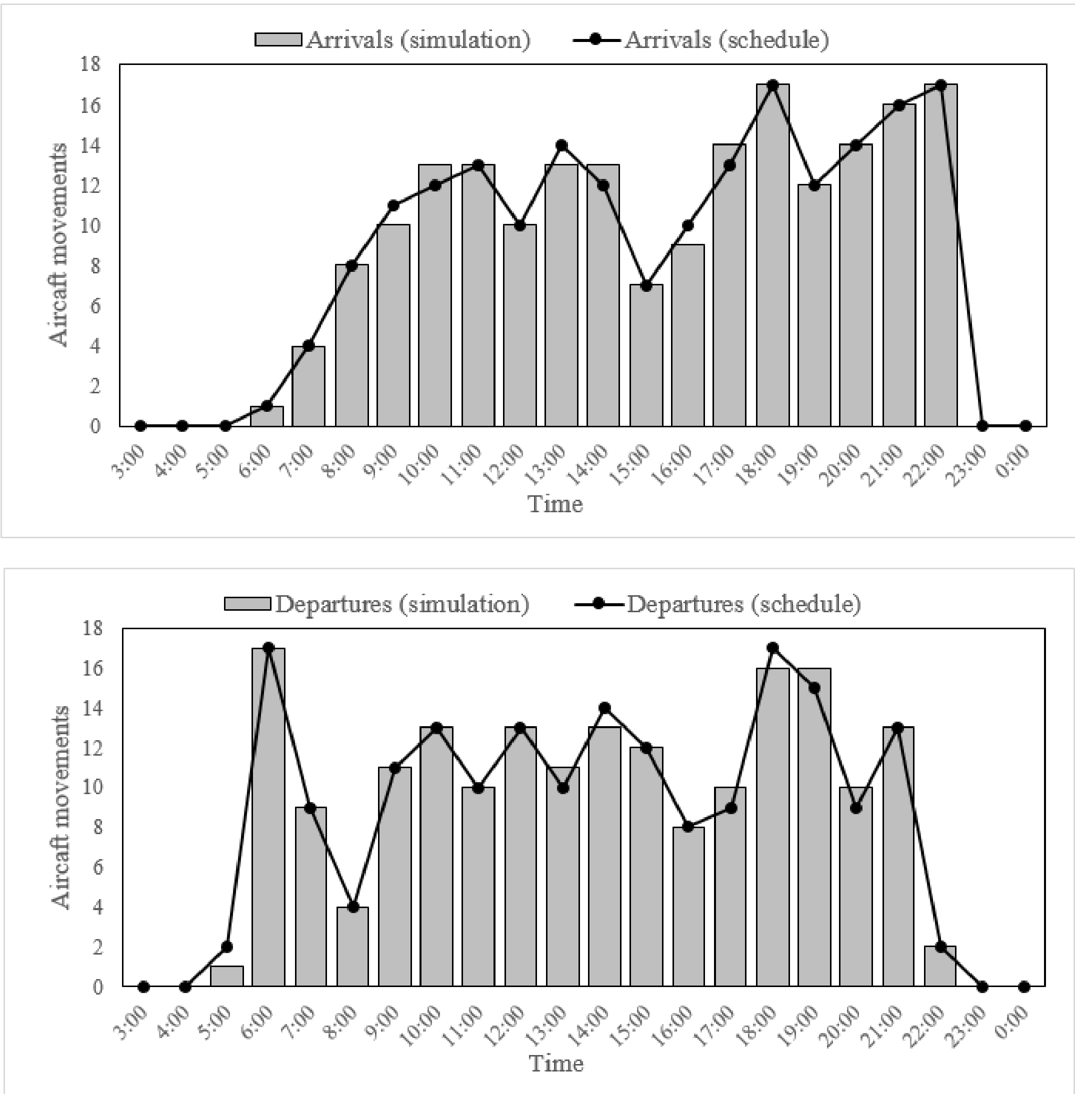


Figure 7.29. Aircraft arrivals and departures

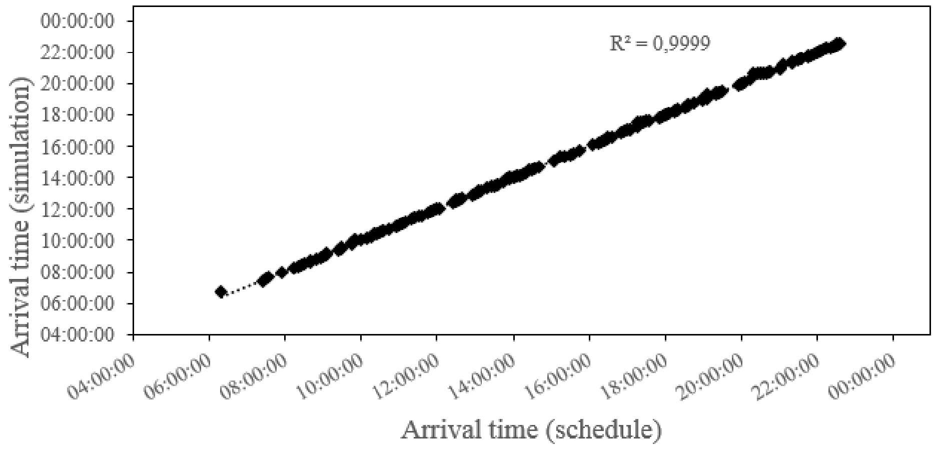


Figure 7.30. STA against ATA

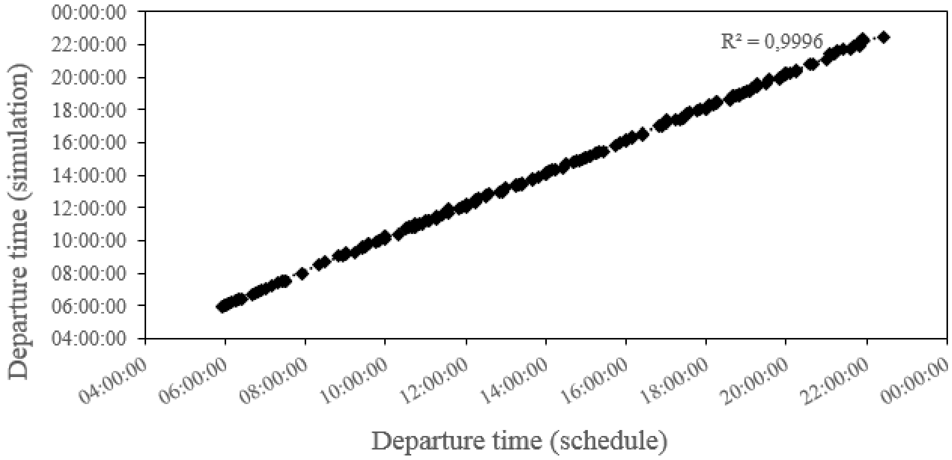


Figure 7.31. STD against ATD

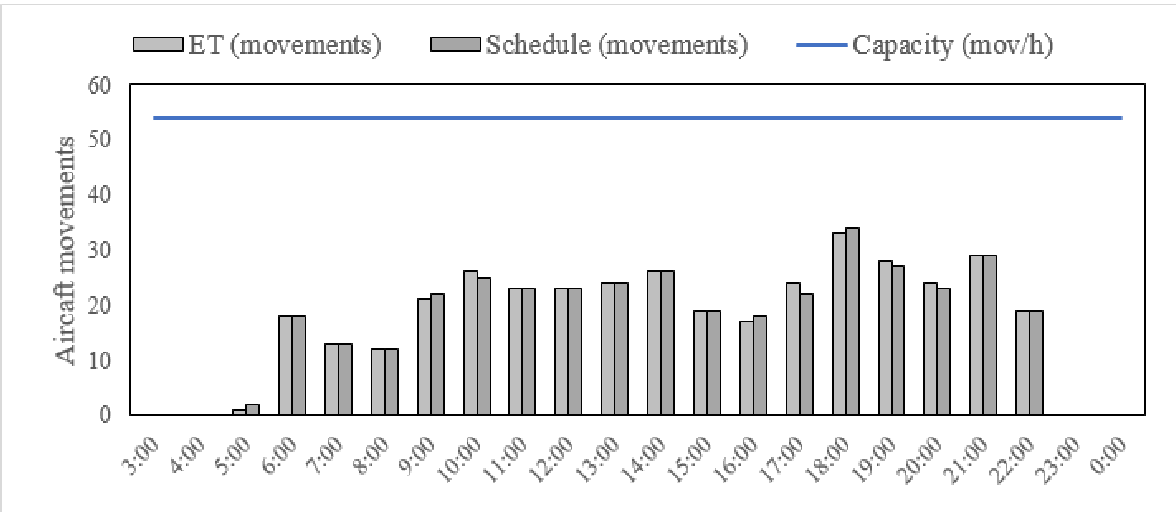


Figure 7.32. Effective Throughput Rate

The histogram in the figure above shows the Effective Throughput $ET_{A,t}$ for the entire simulation period, where $ET_{A,t}$ has been computed in accordance with Eq. 5.8:

$$ET_{A,t} = \sum_{t=1\,hour} n_{DEP} + n_{ARR} \left[\frac{movements}{hour}\right] \quad \text{(Eq. 7.25)}$$

The period of maximum throughput is between 18:00 and 19:00 AM, with approximately 35 movements/hour. However, this value is pretty lower than the capacity of the airport *CAP*, equal to 54 movements/hour and shown in blue in the figure above. The Average Throughput Rate ATR_A during the period of analysis is equal to:

$$ATR_A = \frac{\sum_T ETR_{A,t}}{T} = 65\% \quad \text{(Eq. 7.26)}$$

7.5.3. Disrupted scenario

In the disrupted scenario, a power issue causes the complete closure of the airport for a period T_d = 3 hours, from 10:00 in the morning to 13:00. During this period of time, the capacity of the airport is zero. Thus, from the beginning of the disruption, flights cannot neither land or depart, causing several diversions (30 flights) and cancellations (5 flights) (see Table 7.13). When the disruption is cleared at 13:00 and operations start again, the flights which were not cancelled can take-off with some delays (10 flights). The total impact in terms of movements is then equal to:

$$TI = N_L + N_D + N_C = 45\ flights \quad \text{(Eq. 7.27)}$$

Table 7.13. Disrupted scenario output

	Total	Average	St. Dev.
Departure delay (min)	987.58	98.76	22.38
Arrival delay (min)	314.65	28.60	7.48
Turnaround time (min)	-	42.78	2.47

Impacted flights	
N_L	10
N_C	5
N_D	30

The total departure delay resulted from the simulation is equal to 987.58 minutes, with an average of almost 99 minutes. This value is in line with the delay information registered by

EUROCONTROL (1,012 minutes, see Table 7.1), with a slight variation of 3%. This result confirms the validity of the model and its capability of correctly reproducing the disrupted scenario. In terms of turnaround, no significant increase has been experienced by the and the Turnaround Loss TL is then equal to 0:

$$TL = \frac{\overline{TAT}_D\ (m|J_{mP}) - \overline{TAT}\ (m|J_{mP})}{\overline{TAT}\ (m|J_{mP})} = 0\% \qquad \text{(Eq. 7.27)}$$

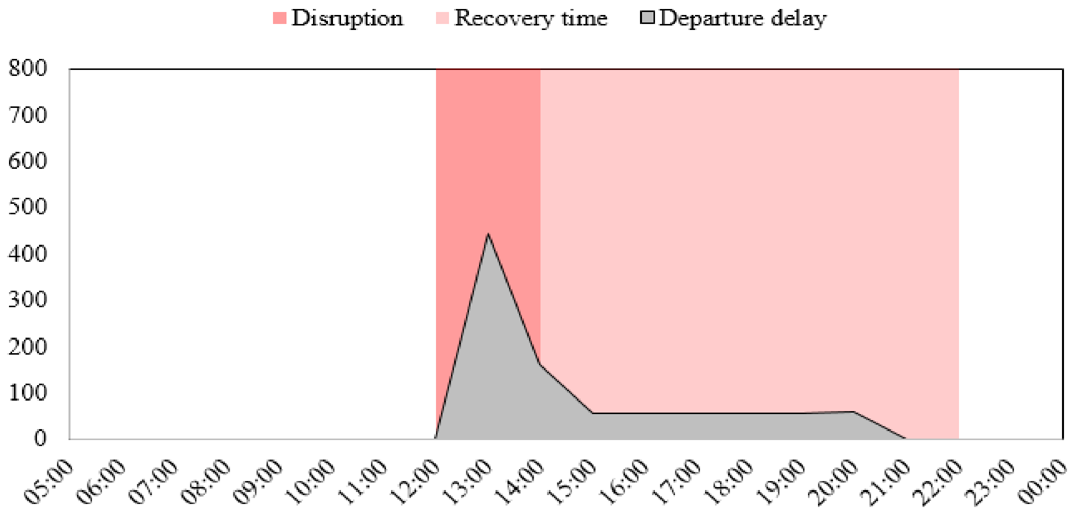


Figure 7.33. Departure delay

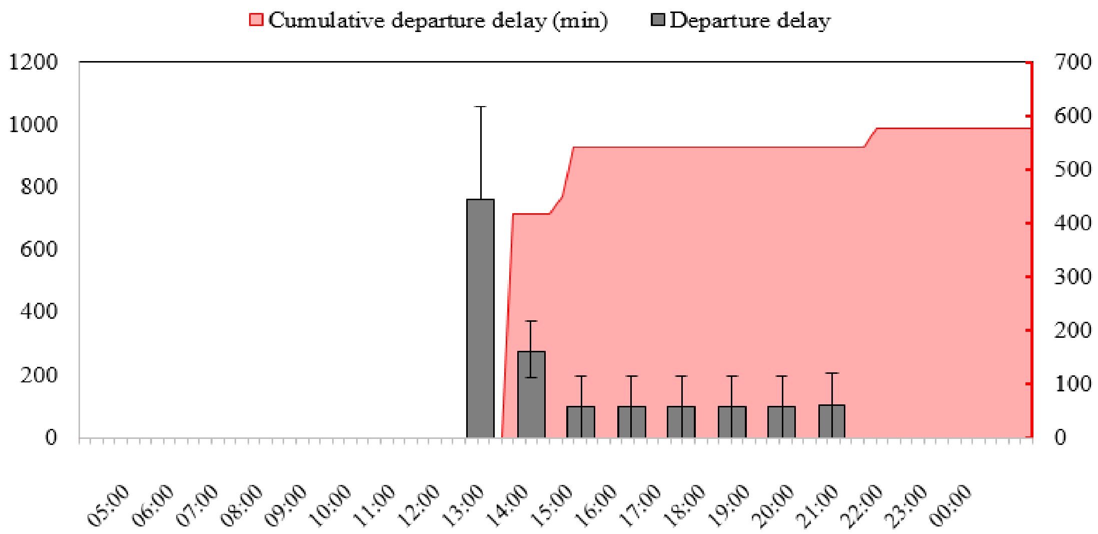


Figure 7.34. Cumulative departure delay

Figure 7.33 illustrates the delay per hour of simulation (in grey). During the closure (in red in figure), no delay is observed as the airport is closed and flights cannot depart. At the end of the disruption, flights start departing again and some delays are experienced. Knock-on delays are observable until 21:00, 8 hours after the end of the disruption, when the system returns to function normally. The total duration of the disruption is then equal to:

$$t_t = t_d + t_r = 3 + 8 = 11 \ hours \qquad \text{(Eq. 7.28)}$$

The graph in figure 7.35 depicts the cumulative Effective Throughput Rate through the entire day of analysis in both the baseline (grey) and disrupted scenarios (blue). The figure below shows the same indicator, but on an hourly basis. From the latter figure, it is cleared that ET is equal to zero as long as the airport is closed. When operations start again, the Effective Throughout Rate is slightly higher than the baseline one, as aircraft (not cancelled nor diverted) that were scheduled to land or depart during the airport closure, at this point can perform such operations. The Capacity Loss CL is evaluated, as in the cases before, as the difference between the baseline Average Throughput Rate ATR_A and the disrupted Average Throughput Rate ATR_D during the entire simulation period:

$$CL = ATR_A(t_t) - ATR_{A,D}(t_t) = \frac{\sum_{tt} ETR_{A,t}}{t_t} - \frac{\sum_{tt} ETR_{A,D,t}}{t_t} = 0.46 - 0.35 = 0.11 = 11\% \qquad \text{(Eq. 7.29)}$$

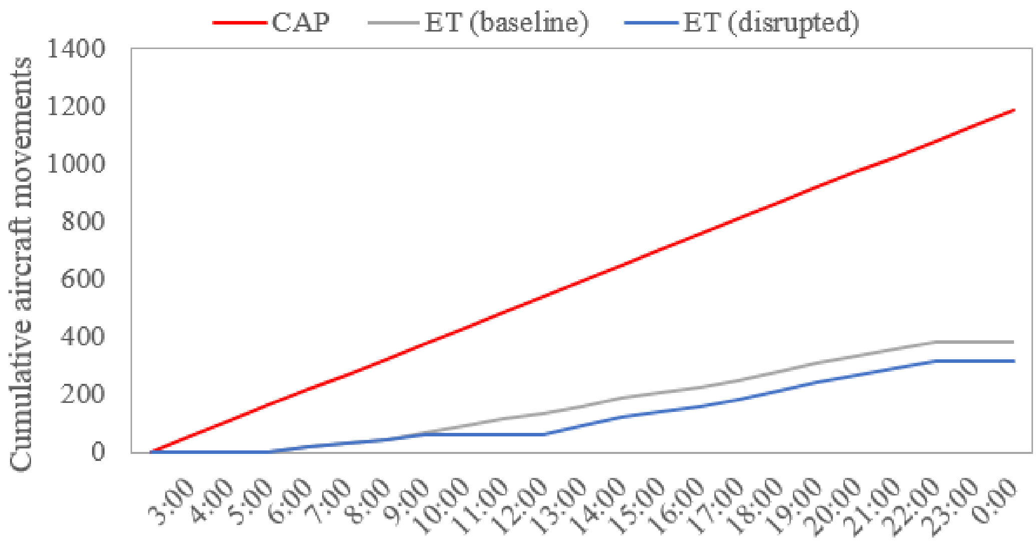


Figure 7.35. Cumulative Effective Throughput Rate

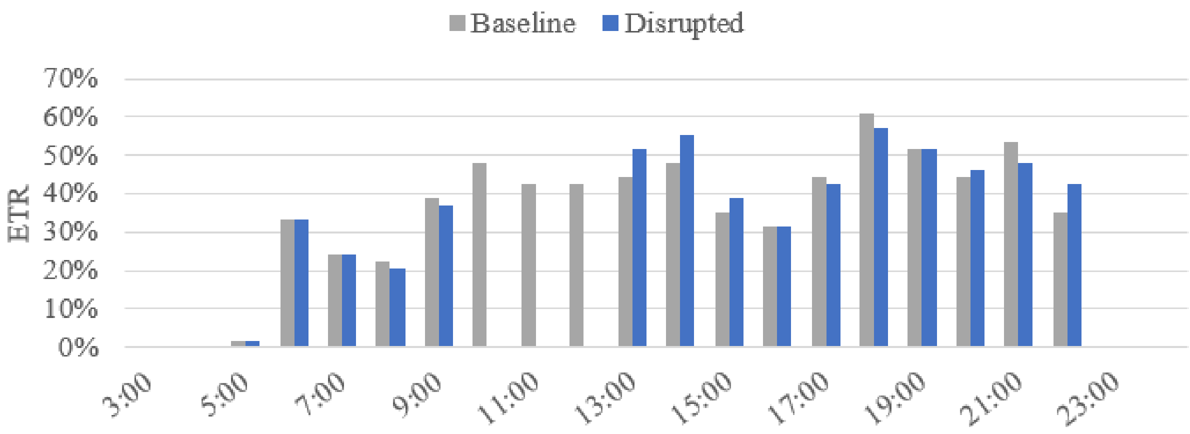


Figure 7.36. Effective Throughput Rate

Also in this case, resilience and vulnerability indicators are evaluated to get synthetic measures of the consequences of the disruptive event and compare them with other scenarios. Vulnerability is then evaluated according to Eq. 5.32:

$$V_{A,D} = \beta_L N_L + \beta_D N_D + \beta_C N_C = 0.56 * 10 + 0.42 * 30 + 1 * 5 = 23\ flights \qquad \text{(Eq.7.30)}$$

Were weights β_i are evaluated with respect to the cost of a cancelled flight $COST_C$ (see Chapter 4):

$$\beta_L = \frac{COST_L}{COST_C} = \frac{100 * \overline{DEL_{DEP}}}{17{,}650} = 0.56$$

$$\beta_D = \frac{COST_D}{COST_C} = \frac{7{,}400}{17{,}650} = 0.42$$

$$\beta_C = \frac{COST_C}{COST_C} = 1$$

The resilience is then evaluated as the difference between the baseline and disrupted Average Throughout Rate, both referred to the deviation time:

$$RES = \frac{CL}{t_t} = \frac{ATR_A(t_t)}{t_t} - \frac{ATR_{A,D}(t_t)}{t_t} * 100 = \frac{0.11}{11} * 100 = 1 \qquad \text{(Eq.7.31)}$$

7.6. Discussion

Different disruption scenarios have been simulated, each one belonging to one of the clusters considered in this work. The table below summarized the indicators obtained for each scenario, namely: (1) the duration of the disruption t_d; (2) the recovery time t_r; (3) the total number of delayed, cancelled and diverted flights; (4) the total number of impacted flights; (5) the Capacity Loss *CL*; (6) the Turnaround Loss *TL*; (7) the vulnerability indicator and (8) the resilience indicator.

Table 7.14. Results obtained for the four cases

	A	**B**	**C**	**D**
t_d [h]	7	2.5	8	3
t_r [h]	3	2.5	6	8
t_t [h]	10	5	16	11
N_L [flights]	131	17	50	10
N_C [flights]	0	0	65	5
N_D [flights]	31	0	0	30
TI [flights]	162	17	115	45
CL	0.11	0.12	0.08	0.11
TL	0	0	1.12	0
V [flights]	75	8	97	23
RES	1.1	2.4	0.57	1

Results show that each disruption impact in different ways. Specifically:

- Only in the case of the disruption of Cluster C, turnaround operations are affected, while in the other cases operations are performed as in the base scenario;
- The disruptions of cluster A provokes mainly delays and some diversion;
- For the case of Cluster B, only a few flights are delays, and no cancellations and diversions occur; in this case, the remaining runways of the airport are capable of handling the scheduled traffic and reduce impacts.

- The disruption of cluster C cause principally cancellations; in fact, the increase in turnaround times is such that delays exceed the threshold of 3 hours considered in this work. This is also the scenario with the highest number of impacted flights;
- Regardless of the cluster, in the four cases analysed the Capacity Loss, computed during the entire simulation period, is around 10%.

In terms of vulnerability, the disrupted scenario with the highest value is the one of Cluster C (97), followed by the scenario of Cluster A (75). Recalling that the vulnerability indicator expresses the number of equivalent cancellations caused by the disruption, in these two scenarios monetary costs could be very high. The disruption of Cluster D, even if causing the complete temporary closure of the airport, have a vulnerability indicator quite lower (38). However, is would be highlighted that the vulnerability indicator expresses a quantity in absolute value and is not comparable with other cases; in fact, the number of impacted flights depend on the amount of traffic of the specific airport. For Cluster B, the vulnerability indicator is quite low (8), mainly because the number of impacted flights if quite low as well as the total delay, and no cancellations neither diversions occur.

The different scenarios can be compared by means of the resilience indicators. The higher the value of the indicator, the higher the resilience of the airport system to the specific disruption. Among the four scenarios, the one with the highest value is Cluster B’s scenario, with a value of 2.4. In fact, this is the case with the lower number of impacted flights and the lower recovery time, especially if compared with the duration of the disruption. Conversely, the less resilient scenario is the one of Cluster C, with a value of 0.5. In this case, both the number of impacted flights and the recovery time is very high: the system takes 8 hours to recover, which is the same duration of the disruption. Regarding the remaining scenarios of Cluster A and Cluster D, the resilience indicator is approximatively the same – 1.1 and 1 respectively. Before it was stated that for Cluster D a relatively low value of vulnerability is obtained; however, impacts are quite spread among the day and the recovery time is very high (8 against the 3 hours of disruption). Thus, the resilience indicator takes into consideration also the recovery speed and in this case – due to both the type of disruption and the characteristics of the airport – is not too low. Specifically, it has the same value than Cluster A, which is one of the scenarios which experienced the highest delays and has the highest vulnerability value.

7.7. Simulation of disruptions from 2015 to 2018

From the results presented above, it results that diverse disruptions affect different airport systems in certain ways. However, each case is particularly context-specific, and it is difficult to determine which variables influence resilience and vulnerability indicators. In other words, a high resilience may derive from the type of disruption or from the airport infrastructural characteristics, or from the number of operators and resources deployed.

In order to look for a pattern in the trend of vulnerability and resilience indicators, the simulation model has been used to investigate additional disruptions and different airport. Specifically, the simulation model has been applied to all the airport disruption occurred from 2015 to 2018 in Europe, and registered by EURCONTROL (see Chapter 4), which caused more than 1,000 minutes of ATFM delay.

For each of the disruption, EUROCONTROL's reports provide, in addition to the date and airport of the disruption, the total departure delay for the specific disruption. However, the following variables are necessary to use the simulation model:

1) The duration of the disruption;
2) The capacity reduction caused (depending on the Cluster)
3) The time of the day in which the disruption starts.

These data have been retrieved by searching online information regarding the specific disruption. In many cases, it was possible to find the necessary data. Once find the required input, the simulation model was validated by comparing the total departure delay obtained from the simulation with the total departure delay provided by EUROCONTROL.

Sometimes, one or two of the three information were not available. In these cases, the simulation was run iteratively by changing the unknown variable, until convergence of the total departure delay from simulation's output and EUROCONTROL's reports. If none of the variable was known, the disruption has not been simulated.

At the end, a total of 135 disruption events have been simulated, including disruptions of different types and more 50 different airports. Figure 7. Shows the scatter plot of the total departure delay obtained from the various simulations against the total departure delay provided by EUROCONTROL. By performing a simple linear regression, it results that data present a quite strong positive correlation and the value of the coefficient of determination R^2 is acceptably high (0.9372).

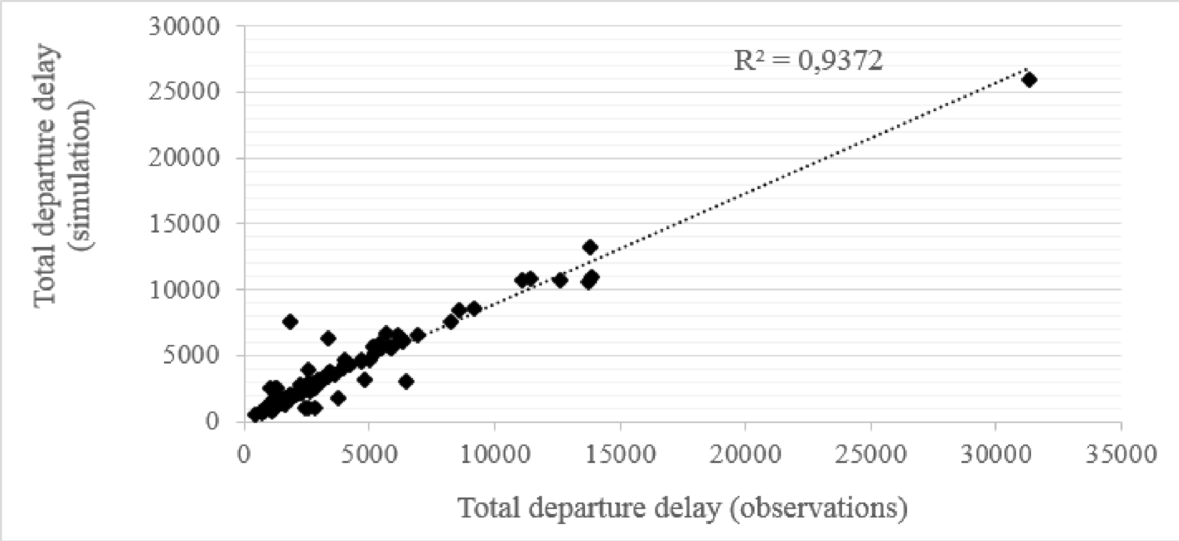


Figure 7.37. Scatter plot of the total delay obtained from the simulations and data provided by EUROCONTROL

By performing these disruptions' simulations, it was thus possible to build a database which includes information about the airport (number of runways, stands, movements per year, number of ground handlers), information regarding the disruption (duration, type, cluster) and results obtained from the simulation (total impact, resilience and vulnerability indicator). Table 6 above shows the characteristics included in the database.

Table 7.15. Information contained in the database

AIRPORT	DISRUPTION	SIMULATIONS' RESULTS
Name	Type	Total departure delay [min]
Movements/year	Cause	Average departure delay [min]
N° of runways	Cluster	N_L, N_D, N_C
N° of aircraft parking stands	Reduced capacity	*TI*
Declared capacity	t_d	Vulnerability *V*
N° of ground handlers		Resilience *RES*

The graphs in figures 7.38 And 7.39 show the vulnerability and resilience indicators per cluster obtained from the 135 simulations. In the majority of cases, the vulnerability indicator is between 5 and 25 flights (more than 50%), while a few cases present a vulnerability very high (higher than 100). Regarding the resilience, the most of scenarios have a resilience lower than 1 (45%). The highest values of resilience are obtained for cluster D (in yellow in figure). The complete database, containing the afore-mentioned information, is provided in Appendix B.

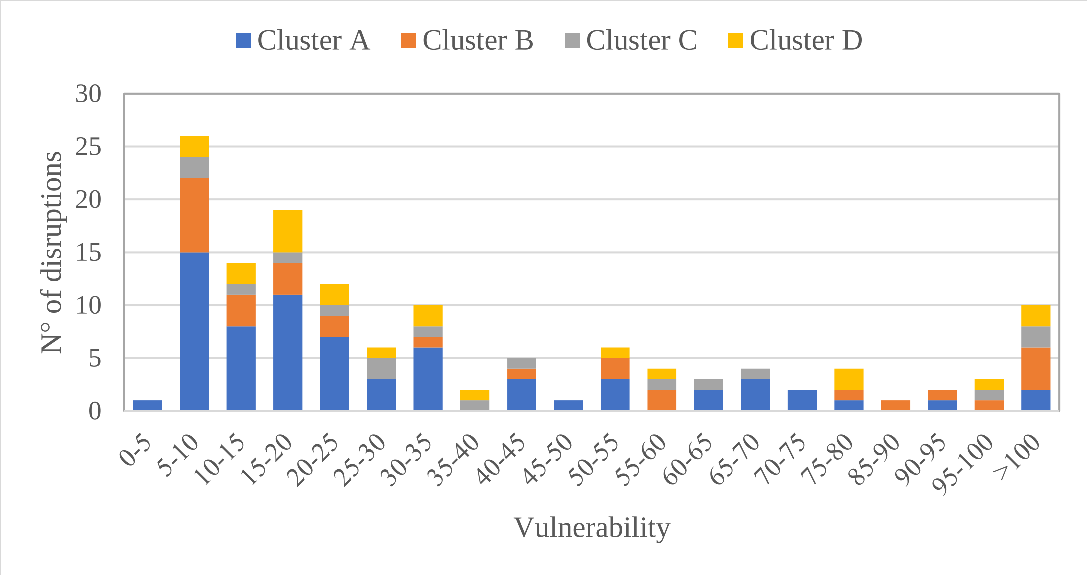


Figure 7.38. Vulnerability values obtained

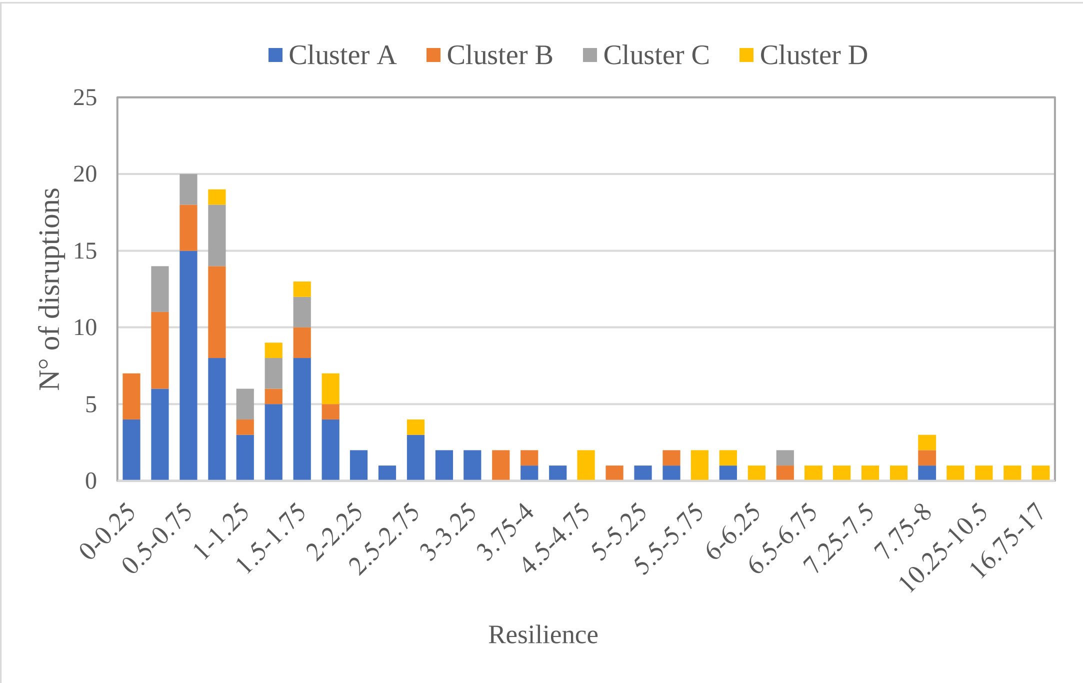


Figure 7.39. Resilience values obtained

8. DISRUPTIONS UNCERTAINTY: A BAYESIAN NETWORK APPROACH

8.1. Introduction

As mentioned before in Chapter 6, airport systems are characterized by intrinsic uncertainties and dynamics which makes airside operations a stochastic phenomenon. This stochasticity is even more emphasized when affected by unexpected disruptive events, which are not possible to predict and may negatively influence the performance in different ways.

The methodology presented and detailed in previous Chapters, enabled to obtain vulnerability and resilience indicators for a large number of disruption cases, affecting different airports with different characteristics. The simulation model allows to take into consideration the inherent dynamics and uncertainties of the considered system and the propagation of delays throughout the operations. The methodology can be successfully used to determine the total performance loss over the entire disruption period, as well as the vulnerability of the system and the recovery time. However, in order to plan strategies to reduce such impacts, it should be advisable to determine which elements – processes and variables – in the system are the most critical, i.e. those causing the highest consequences on the overall functioning of the airside system. Those elements should be the ones to monitor the most, and over which deploy the highest number of (limited) resources. In order to determine such elements, it is fundamental to understand the causal relations between the variables and elements involved in the processes, related to both the disruption and the airport system.

To fill this gap, a method was sought which could determine the probability of the impacts that a disruption might cause on a generic airport, depending on variables related to both the airport and the disruption type and duration. Given the uncertainty of airport operations and disruptions and the intrinsic stochasticity in the disruption management, the most effective method was found in Bayesian Networks. Thus, in the following, a quantification of airport vulnerability and resilience by using Bayesian Networks is proposed.

Bayesian networks (BNs) are graphical probabilistic models which can deal effectively with various uncertainty problems. BNs are a type of probabilistic graphical models that aims at representing the interactions among a set of correlated variables in the form of conditional dependence (and often causation) by using Bayesian inference for probability computation. Structured on Bayes' theorem, they are an excellent tool for computing the posterior probability distribution of unobserved variables conditioned on some variables that have been observed, encoding both quantitative and qualitative information in a conditional probability format (Holmes & Jain, 2008). The structure of a Bayesian network graphically and intuitively represents problems where uncertain variables are modelled as nodes and edges between them represent their conditional dependence. Their construction allows to combine data and expert judgement and inference can be performed efficiently even in models with a large number of variables.

Bayesian networks are effective tools for a wide range of tasks, including prediction, diagnostic, risk assessment, automated insight and, more in general and more importantly, for reasoning and decision making under uncertainty (Neil et al., 2005). They have found popularity in a plethora of disciplines including finance (Habrant, 1999), medicine (Lucas, 2001), law (Vlek et al., 2014), reliability engineering (Neil, 2014). They have been deployed in various studies regarding infrastructure system reliability (Kabir et al., 2015; Sutrisnowati et al., 2015). Several applications can be found in the context of accident analysis (Gregoriades & Mouskos, 2013; Mujalli & De Oña, 2011; De Oña et al., 2011).

In the context of air transport operations, they have previously been applied to cope with different air transport issues, such as the airport operational saturation (Rodríguez-Sanz et al., 2018b), efficiency of air navigation service providers (Bujor & Ranieri, 2016), delay propagation (Laskey et al., 2006) and safety (Morales et al., 2008); (Rodríguez-Sanz et al., 2019) use BNs to assess airport arrivals and departures delays; (Liu et al., 2008) use BNs to explain how subsystem levels causes propagate to provoke system level effects. Despite the prominent popularity in a large variety of studies, BNs have found little application in resilience modelling. For example, (Hossain et al., 2019) utilize BNs to address a range of possible risks to the electrical power system and its independent networks. In (Hosseini & Barker, 2016), a quantification of resilience is proposed in the context of inland waterway ports.

In this study, a Bayesian Network approach is employed to create a probabilistic graphical model which represent the relation between factors influencing airside vulnerability and resilience. By using BNs, it is possible to develop a probabilistic approach to manage uncertainty and assess decision-making, which is consistent with the treatment of stochastic processes.

Bayesian Networks are considered to be an excellent method to assess the resilience of airport's airside resilience for multiple reasons. First of all, BNs allows to model the causal dependencies between the various variable involved and their related uncertainties, thus obtaining valuable insights about the interrelationships among all the factors influencing airside disrupted performance as well as vulnerability and resilience. Secondly, they allow to predict the probability of the consequences of a disruption, given specific evidences. In fact, BNs aggregate the uncertainty from multiple sources for the purpose of managing the system performance and predict the most probable outcome. In our study, the variables to be predicted are the disrupted performance and vulnerability and resilience indicators. Different disruptive scenarios can be simulated in a fast manner, and a sensitivity analysis of parameters can be performed.

8.2. Reasoning under uncertainty

The motivation for constructing a Bayesian network is typically to automate some recurring tasks involving reasoning and decision making under uncertainty, possibly involving extraction of information and knowledge from data.

They are methods to quantify uncertainty by probability. It is quite important to understand the meaning of probability. There are three fundamental interpretations of probability: *frequentist interpretation*, *propensity interpretation* and *subjectivist interpretation*.

In the *frequentist interpretation*, the probability of an event is defined as the limiting frequency of occurrence of this event in an infinite number of trials. For example, the probability of obtaining tails in a single coin toss is the proportion of tails in an infinite number of coin tosses.

According to the *propensity interpretation* the probability of an event is determined by physical, objective properties of the object or the process generating the event (Popper, 1959). For example, the probability of tails in a single coin toss is determined by the physical properties of the coin, such as its two sides and its flat symmetric shape.

The two above-mentioned views of probability are known as “objectivist” as they assume that the probability is an objective property of the physical world. In these interpretations, in order for probability to be a meaningful measure of uncertainty, processes are or have to be imagined as repetitive in nature. However, this is not practical for the majority of real-world applications and for sufficiently complex processes.

The *subjectivist interpretation* overcomes these drawbacks: in this view, also known as Bayesian interpretation or approach, probability of an event is subjective to the personal measure of belief in that event occurring (Hájek, 2012).

In the subjectivist view, probability is interpreted as a measure of personal belief; it is thus legitimate to believe that the probability of heads in a single coin toss is 0.3, just as it is legitimate to believe that it is 0.5. Furthermore, this measure, a personal belief in the event, can vary among various individuals. Even if this interpretation seems to be too loose, this view comes with a rule – known as Bayes' Theorem - for updating probability in light of new observations. It has been proved that if Bayes theorem is used for updating the degree of belief, this degree of belief will converge to the limiting frequency regardless of the actual value of the initial degree of belief. The subjectivist view makes it natural to combine frequency data with expert judgment. This is the interpretation in which Bayesian Networks trace their roots.

8.3. Bayesian Networks

Bayesian networks (also called *belief networks*, *Bayesian belief networks*, *causal probabilistic networks*, or *causal networks*) are directed acyclic graphs (*DAG*) in which nodes represent random variables and arcs represent direct probabilistic dependences among them (Pearl, 2011).

The graph in figure 8.1 represent a generic of Bayesian network with four variables. The structure of the direct graph gives the qualitative part of the BN and indicates relationship between variables: if an arc exists going from variable X_1 to variable X_2, then the value of X_2 depends on the value of X_1. Nodes from which arcs depart are called "*parent*" nodes, while nodes with edges directed into them are called "*child*" nodes. In the example network (figure 8.1), there is an arc from node X_1 to node X_2, thus X_1 is called parent of X_2. Nodes without arcs directed into them are called "*root"* nodes (node X_1 in the figure below), while nodes without a child are referred to as "*leaf nodes*" (node X_4 in the same figure). Cycles in the graphs – i.e. directed paths that start and end at the same point – are forbidden.

Although the graphical structure of the BN provides relevant information regarding the relations between variables, it does not tell much regarding its numerical properties.

The quantitative part of the BN is given by the relations between variables and the corresponding states. The relations between variables are encoded in the form of conditional probability distribution matrices (equivalent to the factors in the factorized form), called conditional probability tables (CPTs), that are associated with the nodes. The Bayesian network then represents the joint probability distribution over the variables of the graph, by taking advantage of conditional independence.

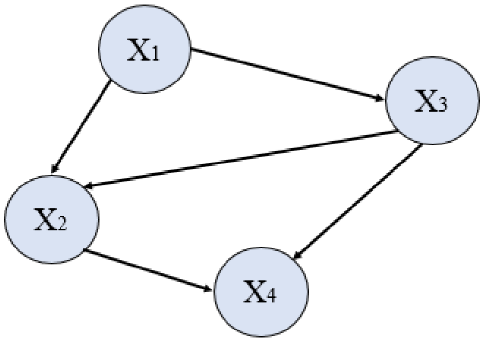


Figure 8.1. Example of Bayesian Network

Every joint probability distribution over *n* variables can be factorized in *n*! ways and written as a product of probability distributions of each of the variables conditional on other variables. For example, in a BN consisting of four variables X_1, X_2, X_3, X_4 the joint distribution of these four variables can be factorized in 4!=24 ways, for example:

$$P(X_1, X_2, X_3, X_4) = P(X_1|X_2, X_3, X_4) * P(X_2|X_3, X_4) * P(X_3|X_4) * P(X_4) \qquad \text{(Eq. 8.1)}$$

$$P(X_1, X_2, X_3, X_4) = P(X_2|X_1, X_3, X_4) * P(X_1|X_3, X_4) * P(X_3|X_4) * P(X_4) \qquad \text{(Eq. 8.2)}$$

$$P(X_1, X_2, X_3, X_4) = P(X_3|X_1, X_2, X_4) * P(X_1|X_2, X_4) * P(X_2|X_4) * P(X_4) \qquad \text{(Eq. 8.3)}$$

And so forth. Each of these factorizations can be represented by a Bayesian network, where arcs between variables represent each of the conditional probability distributions, i.e. arcs from X_2 and X_4 to X_1 represent $P(X_1|X_2, X_4)$. It is worth noticing that there will always be root nodes in the network, i.e. nodes without predecessors. These nodes are characterized by their prior marginal probability distribution. Any probability in the joint probability distribution can be determined from these explicitly represented prior and conditional probabilities.

For a generic Bayesian network with n nodes, the joint distribution of n variables can be expressed as:

$$\begin{aligned} P(X_1, X_2, \dots, X_n) \\ &= P(X_1|\, X_2, X_3, \dots, X_n) * P(X_2|\, X_3, X_4, \dots, X_n) * \dots \\ &* P(X_{n-1}|\, X_n) P(X_n) = \prod_{i=1}^{n} P(X_i|X_{i+1}, \dots, X_n) \end{aligned} \qquad \text{(Eq. 8.4)}$$

Now, suppose that it is known that the variable X_1 and X_4 are independent of each other. Whereas an arc in a Bayesian Network denotes an influence, every independence between a pair of variables results in a missing arc; formally:

$$P(X_1|\, X_4) = P(X_4) \qquad \text{(Eq. 8.5)}$$

Using independencies to simplify the graphical model is a general principle that leads to simple, efficient representations of joint probability distributions, and is one of the key features of Bayesian Networks. Hence, Eq. 8.4 can be further simplified by knowing the parents of each node. In fact, only parents of *Xi* affect the occurrence of X_i:

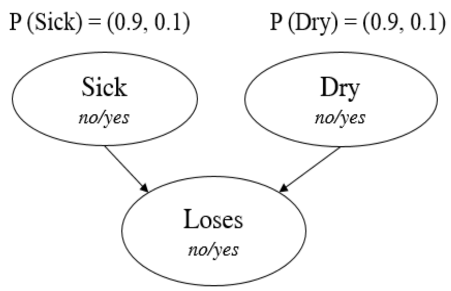
$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} P(X_i|Parents(X_i)) \qquad \text{(Eq. 8.6)}$$

Where $Parents(X_i)$ denotes parent nodes of node X_i. That is, each node is associated with a probability function that takes as input a particular set of values for the node's parents, and gives, as output, the probability distribution of the variable represented by the node.

Consequently, a Bayesian network is a pair (*G*,*P*) where G is the *DAG* defined on a set of *n* nodes X_1 and

$$P = \{P(X_i|Parents(X_i), \dots, (X_n|Parents(X_n)\} \qquad \text{(Eq. 8.7)}$$

Is a set of n Conditional Probability Densities, one for each variable, expresses in the form of Conditional Probabilities Tables (CPT). In a CPT, the rows correspond to states of the random variable modelled by the node; each column corresponds to one combination of outcomes of the parents. An example of CPT is shown in Figure 8.2 for the *Apple Jack network* (Kjaerulff & Madsen, 2008).



		Loses	
Dry	**Sick**	no	yes
no	no	0.98	0.02
no	yes	0.1	0.9
yes	no	0.15	0.85
yes	yes	0.05	0.95

Figure 8.2. Example of CPT table. Source: (Kjaerulff & Madsen, 2008)

Although it is not necessary, a popular and convenient view of Bayesian Networks is that they mimic causal dependence between nodes of the modelled domain. Whereas the structure is causal, it may give valuable insights into the interactions among the variables that it models and allows for prediction of effects of external manipulation. In this perspective, BNs are causal graphs in which every arc represents a direct causal influence between the variable that it connects: a direct arc from X_1 to X_2 imply that X_1 is a causal factor of X_2. Lack of arcs between pairs of variables simply expresses the fact that there is no causal influence between them.

8.4. Bayesian Inference

Bayesian Networks, along with the conditional probability tables associated with their nodes, allow for probabilistic reasoning within the model, i.e. reasoning within the BN when an evidence is observed. A node that have been observed is referred to as "evidence" node, which means that its outcome is known with certainty. The evidence node has an impact and update on the states of other variables in the network, modifying the probability distribution of other nodes that are probabilistically related to the evidence.

The impact can be evaluated by using Bayesian Inference, i.e. computing the impact of observing a value of a subset of the model variables on the probability distribution over the remaining variables. Bayesian inference, also referred to as Bayesian updating or belief updating, derives the posterior probability as a function of a prior probability and a "likelihood function". Bayesian updating, to compute posterior probabilities, is based on a theorem proposed by Rev. Thomas Bayes (1702-1761) and known as *Bayes theorem.* Bayes theorem derives the probability of an event A based on prior knowledge, i.e.:

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)} \qquad \text{(Eq. 8.8)}$$

Where *B* is the evidence and *P(B)* its marginal probability, *P(A)* is the prior probability of the variable that may be affected by the new observation and *P(B|A)* is the conditional probability of *B* given *A*.

Belief updating in Bayesian networks is computationally complex (Cooper, 1990). There exist several efficient algorithms, however, that make belief updating in graphs consisting of tens or hundreds of variables tractable. In general, Bayesian inference techniques can be classified in two different types:

1) Exact inference algorithms;
2) Approximate inference algorithms.

Exact inference algorithms try to derive the exactly posterior probability and they include, among others, the message-passing scheme proposed in (Pearl, 1986), the polytree algorithm (Pearl, 2011), the clustering algorithm (Dawid, 1992; Lauritzen & Spiegelhalter, 1988), the relevance-based decomposition (Lin & Druzdzel, 1997). Among those, the clustering algorithm is one of the faster exact algorithms. It works in two phases: first, a directed graph is compiled into a junction tree, then probability updating is performed in the junction tree. The clustering algorithm, like all of the algorithms for Bayesian networks, produces marginal probability distributions over all network nodes.

However, for very complex graphical models, the time of exact inference becomes prohibitive. In such cases, efficiency can be improved by using approximate inference techniques, which are very effective for particular families of graphical models. Approximate inference includes stochastic simulation and sampling methods.

Approximate algorithms are based on Monte Carlo simulation, in which the model is run through individual trials involving deterministic scenarios. The final result is based on the number of times that individual scenarios were selected in the simulation. Approximate algorithms include, among others, probabilistic logic sampling algorithm (Henrion, 1988); likelihood sampling (Fung & Chang, 1990); backward sampling (Fung & Favero, 1994); EPIS (Estimated Posterior Importance Sampling) sampling (Yuan & Druzdzel, 2003).

Review of Bayesian inference algorithms' can be found in (Henrion, 1990; Huang & Darwiche, 1994; Lin & Druzdzel, 1997).

8.5. Building a Bayesian Network

As described above, a Bayesian network can be described in terms of qualitative components (*DAG*) and a quantitative component (CPTs).

The construction of a Bayesian network model thus consists of the following steps. First, given the problem, the relevant variables have to be identified and the (causal) relations among them: the resulting *DAG* specified dependencies and independencies among variables. This phase is referred to as *structure learning*. In the second phase, given the structure of the BN, relations between variables are described quantitatively, determining Conditional Probabilities Tables for each node. This process is called *parameters learning*.

Both the structure and the numerical parameters of a Bayesian network can be elicited in different ways. BNs can be constructed manually or automatically from data, or through a combination of a manual and data driven process, in which information extracted from databases is blended with experts' knowledge regarding both structure and parameters. Once constructed, parameters of the BN can be continuously updated in the light of new information. In this work, a preliminary Bayesian Network will be built from an external database, and then adjusted, based on model assumptions' and expert knowledge, in order to induce a representative model of the underlying process.

In the following Sections 8.5.1 and 8.5.2 the existing methods to learn both the structure and the parameters from data will be described.

8.5.1. Structure learning from data

Once relevant variables are identified and their domain established, the relations between the variables are elicited, obtaining a *DAG*. Structure learning from data is the task of inducing the graph – i.e. the structure – of a Bayesian network from a source of data (database).

There exist different classes of algorithms for learning the structure of a Bayesian network, such as search-and-score algorithms and constraint-based algorithms, as well as combinations of both. The majority of algorithms are capable of structural learning only if all variables are discrete. In the following, the principal and most used algorithms are briefly described.

The *Bayesian Search* structure learning algorithm is one of the earliest and the most popular algorithms used. It was introduced by (Cooper & Herskovits, 1992) (and follows a hill climbing procedure with random restarts. The algorithm produces the *DAG* that gives the maximum score, which is proportional to the probability of the data given the structure.

The *PC* structure learning algorithm is one of the earliest and the most popular algorithms. It uses independences observed in data (established by means of classical independence tests) to infer the structure that has generated them (Spirtes & Meek, 1995). This is the only algorithm which allows for learning the structure when all variables are continuous.

The *Greedy Thick Thinning* (*GTT*) structure learning algorithm is based on the *Bayesian Search* approach. *GTT* starts with an empty graph and repeatedly adds the arc (without creating a cycle) that maximally increases the marginal likelihood until no arc addition will result in a positive increase (Chen et al., 1997). Then, it repeatedly removes arcs until no arc deletion will result in a positive increase in marginal likelihood.

The *Tree Augmented Naive Bayes* (*TAN*) structure learning algorithm is a semi-naive structure learning method based on the *Bayesian Search* approach (Friedman et al., 1997). The *TAN* algorithm starts with a *Naive Bayes* structure (i.e., one in which a chosen class variable is the only parent of all remaining, feature variables) and adds connections between the feature variables to account for possible dependence between them, conditional on the class variable.

However, it should be highlighted that none of the algorithms allows for learning from data with constant values or from a mixture of discrete and continuous variables, so if there is a discrete variable in the learning set, it is necessary to discretize all continuous variables. Moreover, only the Naive Bayes algorithm is capable of learning the structure of a model when there are missing values in the records.

8.5.2. Parameters learning from data

Parameters estimation in a BN is the task of estimating the conditional probability distributions for the given structure from a database. Parameter estimation is usually performed by using the Expectation-Maximization (EM) algorithm (Lauritzen, 1995). The EM algorithm calculate the maximum likelihood (ML) and maximum a posterior estimates (MAP) by iterating two steps: the expectation E-step and the maximization M-step. The premise of the Maximum Likelihood approach to find parameters that maximize the likelihood (or probability) of the observed data.

The EM algorithm starts with randomly assigning an initial configuration θ^0 to the parameters of the system. The E-step consists of computing the expected value of the log-likelihood function of θ with respect to the current set of observed data X and the current estimates of the parameters θ^t:

$$Q(\theta|\theta^t) = E_{X,\theta^t}[\log L(\theta, X, Z)] \quad \text{(Eq. 8.9)}$$

Then, the M-step computes the parameters that maximize $Q(\theta|\theta^t)$:

$$\theta^{t+1} = \operatorname{argmax} Q(\theta|\theta^t) \quad \text{(Eq. 8.10)}$$

These two steps are repeated iteratively until convergence or until a maximum number of iterations is reached.

8.6. Construction of the Bayesian Network

In this work, the Bayesian Network has been constructed by using the software GeNie[1]. GeNie Modeler is a development environment for building graphical decision-theoretic models (https://www.bayesfusion.com/genie/). The software was created and developed by the University of Pittsburgh, between 1995 and 2015. GeNIe has been originally developed to be principally a teaching and research tool in academic environments; nowadays, because of its reliability and versatility, it has become very popular for both academic and commercial users.

To build the Bayesian Network, a data-driven modelling approach has been adopted. The data-driven process is composed of two phases. In the first one, the structure and parameters of the network are learnt from a source of data (database). In the second phase, the model is adjusted in accordance with model's assumptions and expert knowledge. Once the network has been constructed and validated, some evidence can be propagated, and observations can be derived. The data-driven modelling approach is illustrated in figure 8.3.

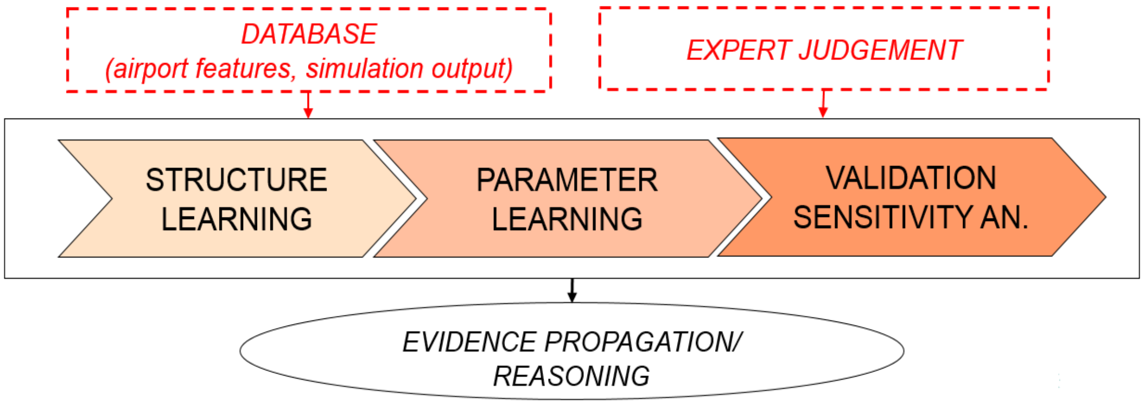


Figure 8.3. Phases of the BN modelling

The first step in the construction of the Bayesian Network is to select the variables of interest, that will constitute the nodes of the BN. In this case, variables of interest are those which may influence the airside airport performance when affected by certain types of disruption and consequently the system's vulnerability and resilience. The choice of the variables to be included in the Bayesian Network derives from several discussions with expert of the field, including both airport operators and academics.

[1] Available free of charge for academic research and teaching use from BayesFusion LLC, https://www.bayesfusion.com/

As a result, three main groups of variables have been chosen. The first one is related to the airport characteristics and include; number of runways, declared capacity, movements per day, number of aircraft parking stands and ground handlers. The second group includes variables describing the disruption, i.e. the cluster, the cause, the duration and the capacity reduction imposed on the system. The last group of variables is related to the impacts caused by the disruption, namely the number of delayed, cancelled and diverted flights, the total departure delay and the Capacity Loss (*CL*) provoked. Moreover, two additional variables are considered, i.e. the vulnerability and resilience indicator. In this case, 17 variables have been chosen, and they are illustrated in Figure 8.4.

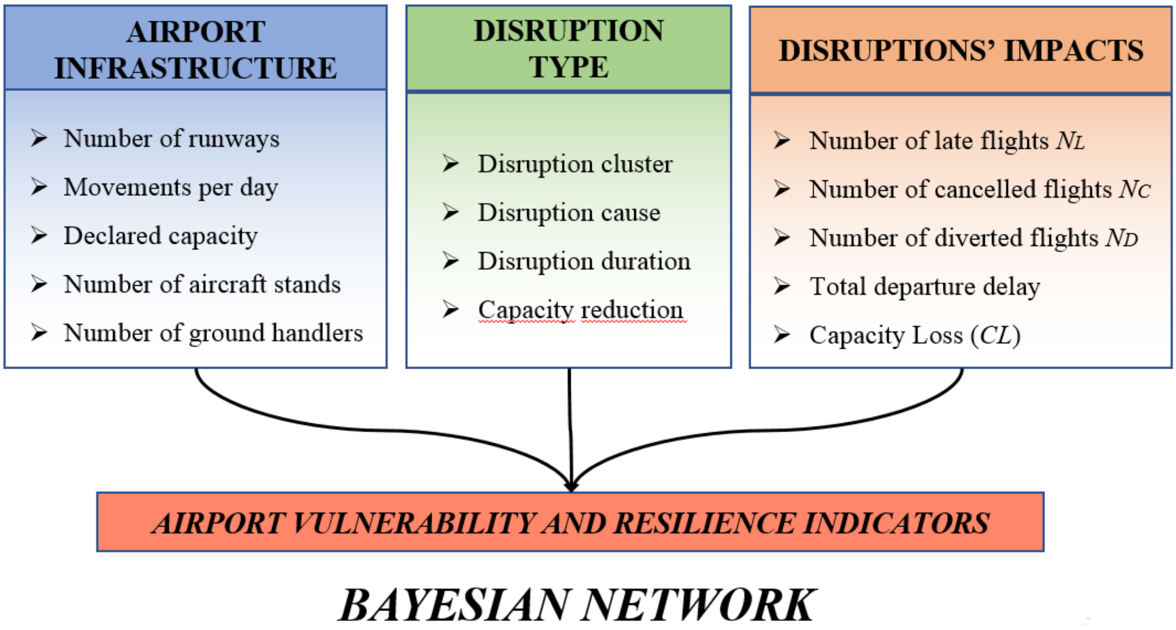


Figure 8.4. Variables included in the Bayesian Network

The database used to build the Bayesian Network in built from the disruption's database described in Section 7.8, which was developed for the 135 disruptions which affected European airports in the last years. The database includes all the variables needed to build the network.

Then, as second step, a correlation matrix has been generated for the variables involved, in order to assess the correlation between them. The correlation matrix can be seen in figure 8.5, where strong positive correlations are shown in green, while strong negative correlations are in red. The strength of the correlation is indicated by the length of the bar.

	ï»¿RUNWAY	DECLARED_CAPACITY	MOVEMENTS_DAY	AIRCRAFT_STANDS	GH	REDUCED_CAPACITY	Td	DELAY_TOT	NL	NC	ND	Tr	Tt	CL	LOSS	RESILIENCE
ï»¿RUNWAY	-															
DECLARED_CAPACITY	0.827508	-														
MOVEMENTS_DAY	0.750087	0.922705	-													
AIRCRAFT_STANDS	0.449283	0.74795	0.71795	-												
GH	0.272771	0.272662	0.215225	0.206525	-											
REDUCED_CAPACITY	0.0796984	0.0711835	0.094696	0.132124	0.0887421	-										
Td	-0.276049	-0.42961	-0.444801	-0.30521	-0.233973	0.170368	-									
DELAY_TOT	0.329882	0.323476	0.400277	0.222101	0.0101519	0.217983	0.0992793	-								
NL	0.390304	0.400599	0.474247	0.260116	0.0385871	0.169971	0.110024	0.937124	-							
NC	-0.0999309	-0.0427752	-0.0263525	0.0259127	-0.184028	0.167168	0.075821	0.114929	-0.0284...	-						
ND	0.0391666	0.161287	0.197449	0.152167	0.0839283	-0.0495299	0.0713221	0.199552	0.155722	0.0100...	-					
Tr	0.207432	0.172398	0.14762	-0.0442677	0.135715	-0.0511696	-0.255523	0.241855	0.231792	0.0382...	0.142296	-				
Tt	-0.154808	-0.325464	-0.354325	-0.324934	-0.153748	0.138733	0.839503	0.233528	0.238435	0.0960...	0.150089	0.310805	-			
CL	-0.202284	-0.0580517	0.102702	0.052408	-0.110233	-0.0288165	-0.150766	0.195256	0.0866...	0.455246	0.488755	-0.2215...	-0.2727...	-		
LOSS	0.0525753	0.137286	0.190498	0.147912	-0.109323	0.194378	0.122975	0.520372	0.374405	0.836837	0.425485	0.166769	0.214625	0.60342	-	
RESILIENCE	0.0414264	0.202052	0.283279	0.22919	0.0670284	-0.068646	-0.485556	0.00392758	-0.0807...	0.128522	0.308205	-0.2331...	-0.6083...	0.763855	0.209349	-

Figure 8.5. Correlation matrix

It is possible to notice that variables indicating airport characteristics (runways, movements/day, aircraft parking stands and declared capacity) are strongly positively correlated. Also the number of delayed flights N_L strictly depends on the dimension of the airport (number of movements and capacity) and on the total delay, as it was reasonable to expect. Besides, the duration of the disruption t_d presents a strong negative correlation with respect to airport related variables. These information regarding the correlation between variables (or information regarding no correlation between variables) will be used while defining the structure of the Bayesian Network.

Subsequently, a data-driven process was used to build the BN, by means of the Bayesian Search Algorithm (BS), which was described in previous Section. The *BS* algorithm produced a preliminary graph, which was then adjusted by means of expert's knowledge. Then, parameters learning was performed by means of the EM algorithm (described in Section 8.5). In order to verify the goodness of the model, it was validated by using cross-validation. The network was iteratively refined until an acceptable level of accuracy was reached.

The Bayesian Network obtained is shown in figure 8.6 and 8.7. Two different types or node are used. Chance nodes, drawn as circles or ovals (such as nodes *Runways* and *Cluster*) are random variables and they represent uncertain quantities that are relevant to the decision problem. They are quantified by conditional probability distributions. Equation nodes are continuous chance nodes, whose interaction with their parents can be described by means of an equation. Equation nodes are drawn as ovals with a wave symbol (such as node *Resilience*), denoting that they can take continuous values. Instead of a conditional probability distribution table, which describes the interaction of a discrete node with its parents, an equation node contains an equation that describes the interaction of the equation node with its parents. The equation can contain noise, which typically enters the equation in form of a probability distribution.

Variables belonging to the same group are coloured the same: nodes referring to airport characteristics are all green, nodes related to the disruption are blue-coloured and nodes referring to the disruptions' impact are in orange. The thickness of the edges symbolizes the strength of influence between the nodes that they connect. In figure 8.7, the strength of influence is evaluated by measuring the Euclidean distance between the conditional probability distributions of each pair of nodes.

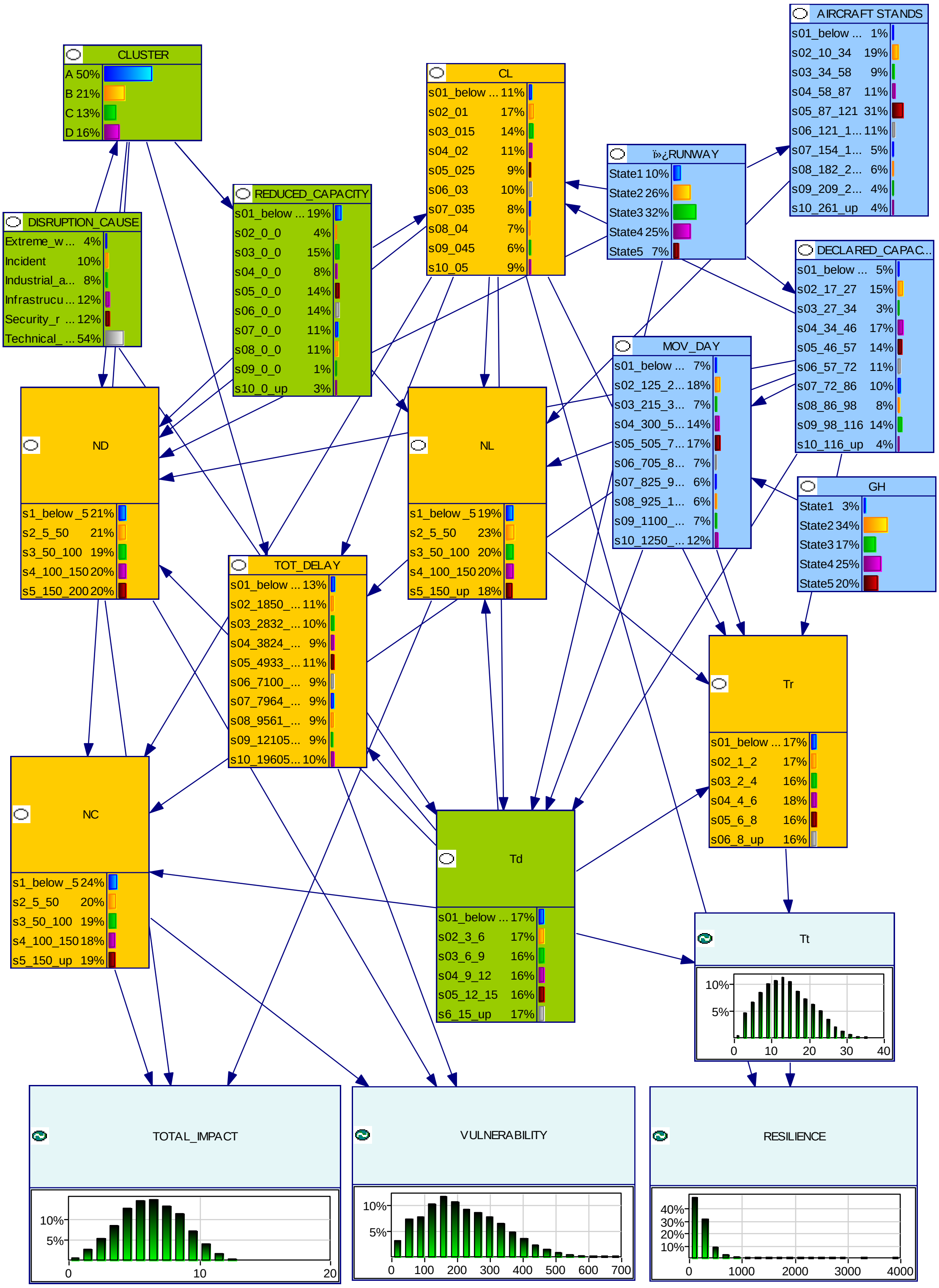


Figure 8.6. Bayesian Network for resilience evaluation

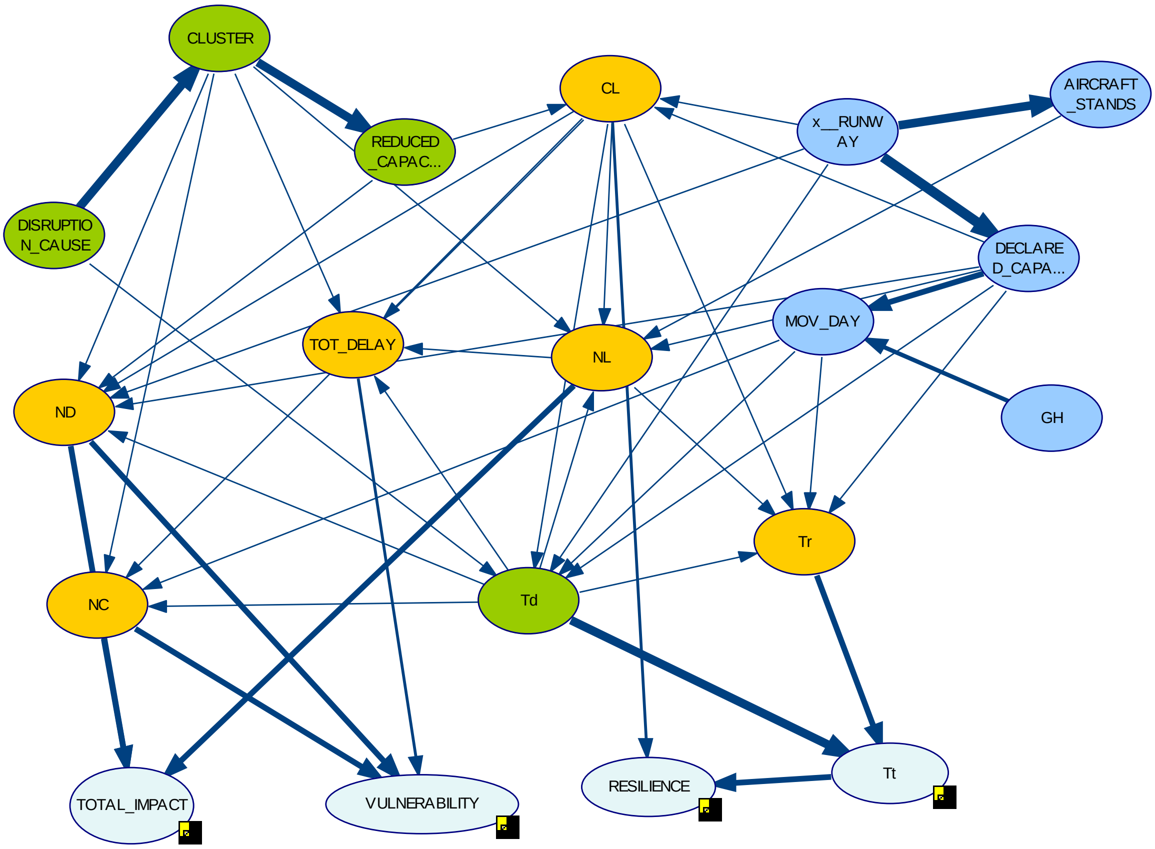


Figure 8.7. Strength of influence in the BN

Figure 8.8 shows two ROC Curves (Receiver Operating Characteristic) which expresses the quality of the model by plotting the true positive rate against the false positive rate at various thresholds. The best predictability is obtained when the curve reaches the upper left corner of the graph. However, points above the diagonal line represent good accuracy results. Above the curve, the Area Under the ROC Curve (*AUC*) is displayed, which is a simple indicator which expresses the quality of the model. Each ROC refers to one state of one variable. In the figure 8.8, ROC curves are shown for predicting (a) the value of CL between 0.15 and 0.20 and (b) the value of the total departure delay between 7100 and 7964 minutes.

Once built the Bayesian Network, it can be used as a decision-making tool for disruption management. It allows to predict resilience and vulnerability values by setting the probability of having a certain configuration.

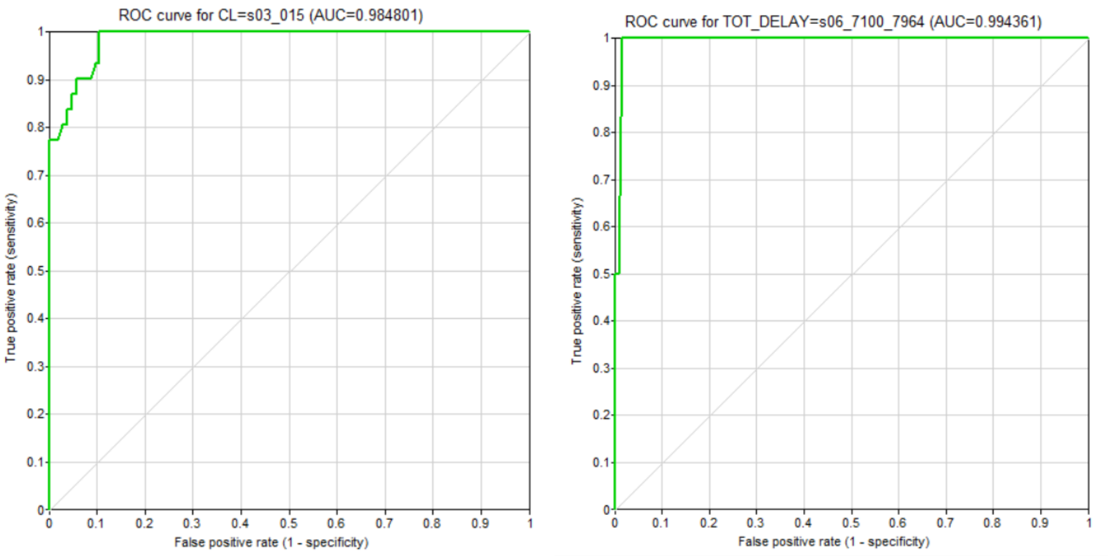


Figure 8.8. ROC curves for specific states of (a) CL and (b) TOT_DELAY

9. CONCLUSIONS

The efficiency of airport operations is often compromised by unplanned disruptive events of different kinds, such as bad weather, strikes or technical failures, which negatively influence the punctuality and regularity of operations, causing serious delays and congestion. The research field related with the risk of severe air transport network disruptions and their impact on society is related to the concepts of "vulnerability" and "resilience".

The aim of this work was to provide a framework that allows to evaluate the performance losses and consequences due to unexpected disruptions on airport airside operations and determine the resilience and vulnerability of the system. Resilience describes the ability of a system to cope with such circumstances and recover from them, while vulnerability refers to the impacts of unexpected disruptive events that could undermine the whole system.

Resilience is a concept which has been largely addressed in the past few years, and several qualitative and some quantitative interpretations have been proposed, without reaching an unambiguous definition. Among all the different definitions, what is clear is that resilience consists of several capacities and properties which allows the system to cope with unexpected disruptions. Specifically, a resilient system has both the capacity of minimizing the impacts of a disruption and the ability to recover to the fully operational level within the shortest time possible. Regarding airport airside operations, resilience is a topic which has not been adequately addressed in the literature. Only a handful of studies tried to determine the impacts caused by an unexpected disruption on airside operations, however restricting the analysis to specific processes or disruptions.

This thesis builds on existing literature by proposing a general framework to evaluate resilience and vulnerability indicators which considers in a comprehensive way all main airside processes, including their stochasticity and dynamics; such framework could be easily applied to airport with different characteristics and different types of disruptions. Resilience has been here defined as the "*airport's ability, during and immediately after the occurrence of a disruptive event, to reduce efficiently both the magnitude and duration of the deviation from targeted operational performance levels*", while vulnerability indicates the magnitude of the impacts caused by the disruption. In accordance with these definitions, resilience and vulnerability indicators has been defined which depend on the loss of capacity during the disruption. Vulnerability has been evaluated as the number of equivalent cancelled flights during the disruption, where delayed, cancelled and diverted flights have been weighted based on their costs; besides, the resilience indicator is a function of both loss of runway throughput and the recovery time.

Airside operations have been modelled as a function of the available resources and taking into consideration their stochastic and time-varying nature, which create a set of dynamics that influence the way the system evolves over time. Four clusters of disruptions have been modelled, depending on the operations directly affected. The impacts caused on airside operations are evaluated by using a stochastic simulation model that allows to determine the propagation of delays throughout the simulation period. The simulation model generates outputs of time-dependent measures of performance at different levels and allows to determine delays and the recovery time of the system. The vulnerability and resilience indicators obtained allow to compare different disruption scenarios and assess the difference among the responses of different airports with different characteristics.

The simulation model can be successfully used to determine the total impact of a disruption as a function of time. However, in order to develop strategies to mitigate such negative consequences, it is essential to determine which processes are the most critical and causing the highest impacts on the overall performance. In this sense, it should be advisable to understand the causal relationships between the involved variables, in order to determine elements on which invest or to monitor the most.

Thus, a quantification of airport vulnerability and resilience of airport airside operations by using Bayesian Networks is proposed, in order to determine the probability of the impacts that a disruption of a certain type might cause on a generic airport. The use of Bayesian Networks allows, on one side, to understand the causal relationships between the variables involved and the consequences of an unexpected disruption; on the other side, such tool can be used to predict the impacts of certain types on disruptions.

Bayesian Networks allows to combine historical data and expert knowledge, using calculation of prior and posterior conditional probability. They provide a rigorous tool for handling decision making under uncertainty, which is the case of airport disruptions. Moreover, BNs have the advantage to graphically represent the dependences among the variables in the system. Although Bayesian Networks have proven to be useful in a number of fields, their application to quantify resilience is still limited. The Bayesian Network has been built by means of a data driven process, in which information extracted from databases is blended with experts' knowledge regarding both structure and parameters. The variables included in the network express airport features, disruption characteristics and parameters related to the impacts of the disruption, such as the total departure delay and the loss of capacity, as well as resilience and vulnerability indicators. Once built the Bayesian Network, it can be used as a decision-making tool for disruption management: it allows to determine the strength of influence of the different airport elements on the resilience/vulnerability of the system, and allows to predict (i.e. determine the effects) resilience and vulnerability values by setting the probability of having a certain configuration. Then, it can be used to determine the elements on which invest resources – which are limited in number – in order to increase the resilience of the system.

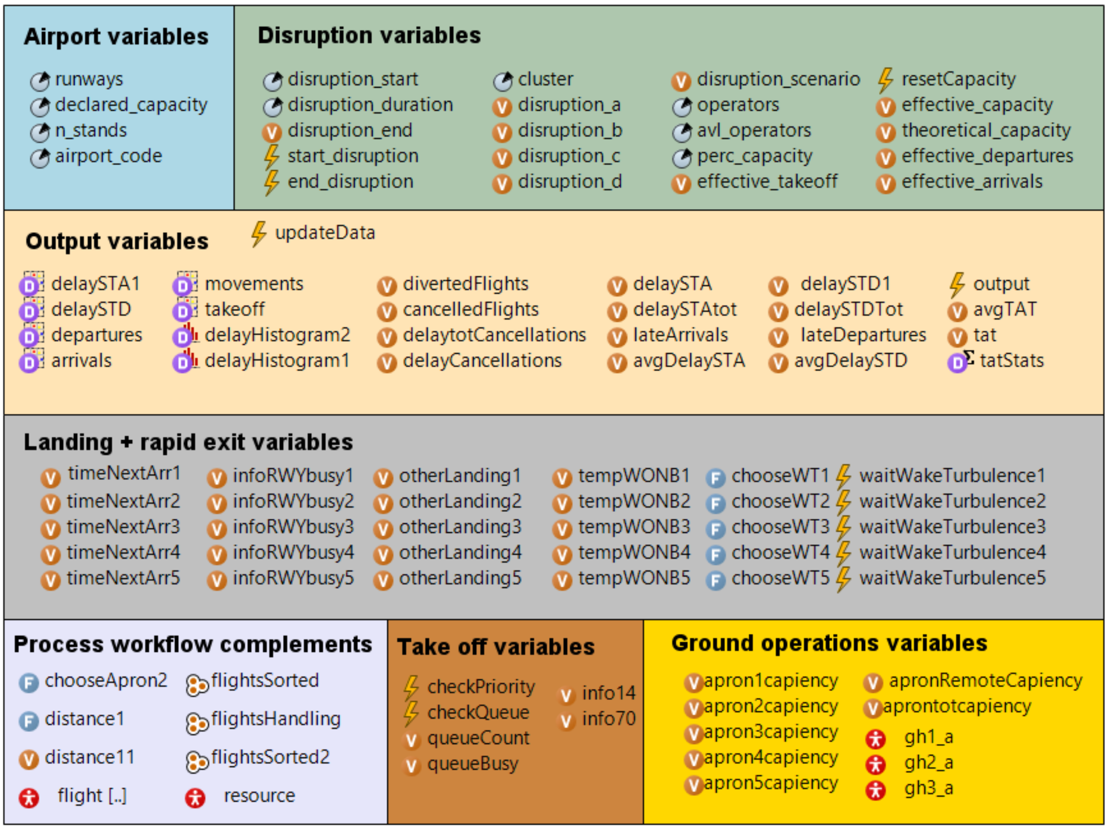
Summarizing, the main contributions of this thesis to existing literature are the following:

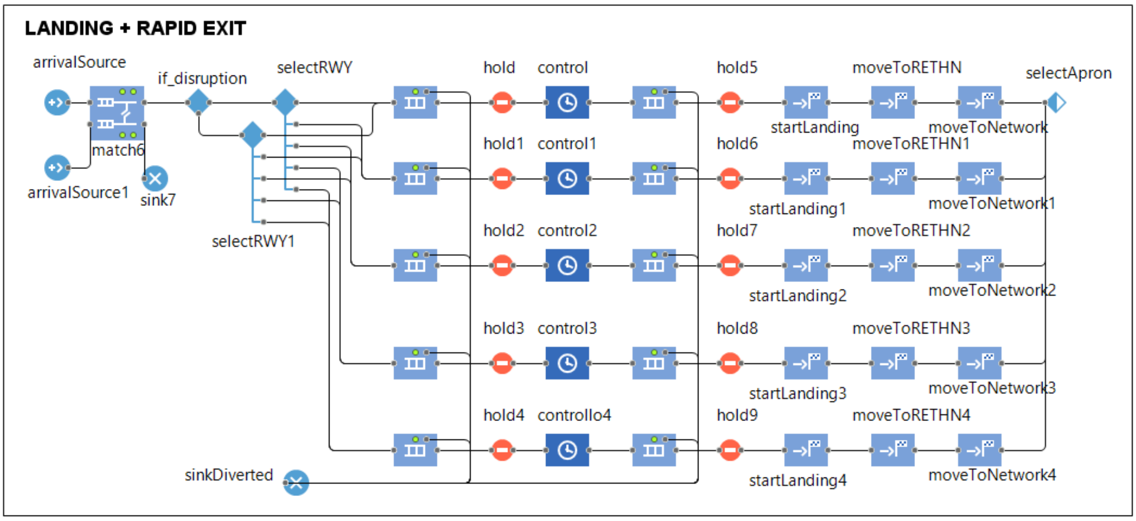
- First, the methodological approach proposed is based on a simulation model in which the uncertainty and stochastic nature of in airside processes is taken into consideration, thus allowing to evaluate knock-on delays as a function of the amount of the available resources;
- Second, this thesis addressed the topic of resilience in airside operations which has not been adequately addressed in the literature, despite the importance of the topic;
- Third, resilience and vulnerability indicators are proposed for airside operations which depends on both the vulnerability and the recovery time of the system;
- Last, a novel approach to evaluate the resilience of a system has been proposed by using Bayesian Networks, which permit to determine the most influencing elements of the system and to predict the probability of having certain consequences.

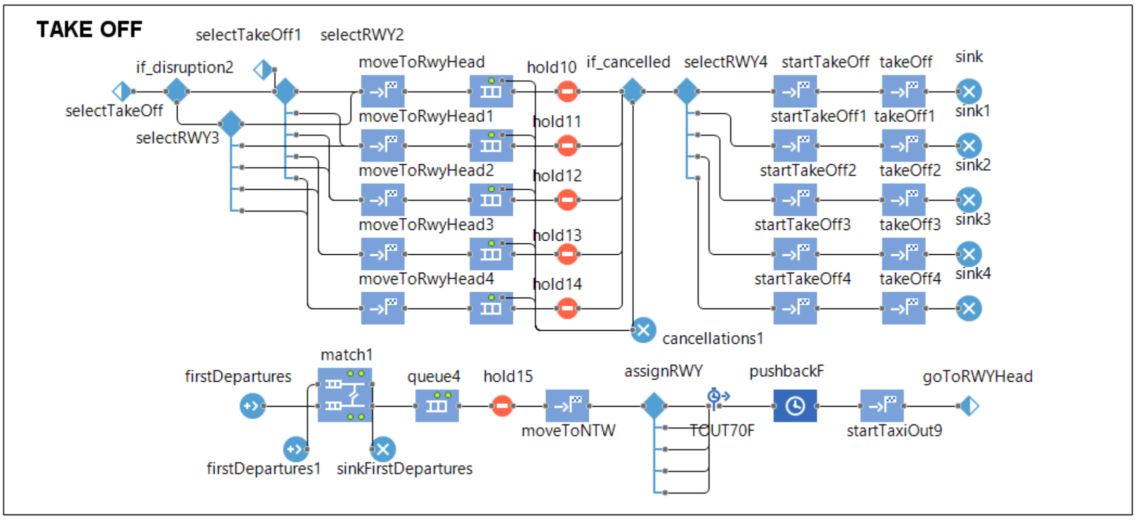
However, this work is not without limitations. First of all, the potential of the Bayesian Network has not been fully exploited yet. Several scenarios can be investigated to further understand the dependencies between variables and develop strategies to mitigate disruptions' impacts. Moreover, the database used to build the Bayesian Network is limited in number. Even if there is no minimum number required to build BNs from an external database, a higher number of data should certainly increase the accuracy of the model.

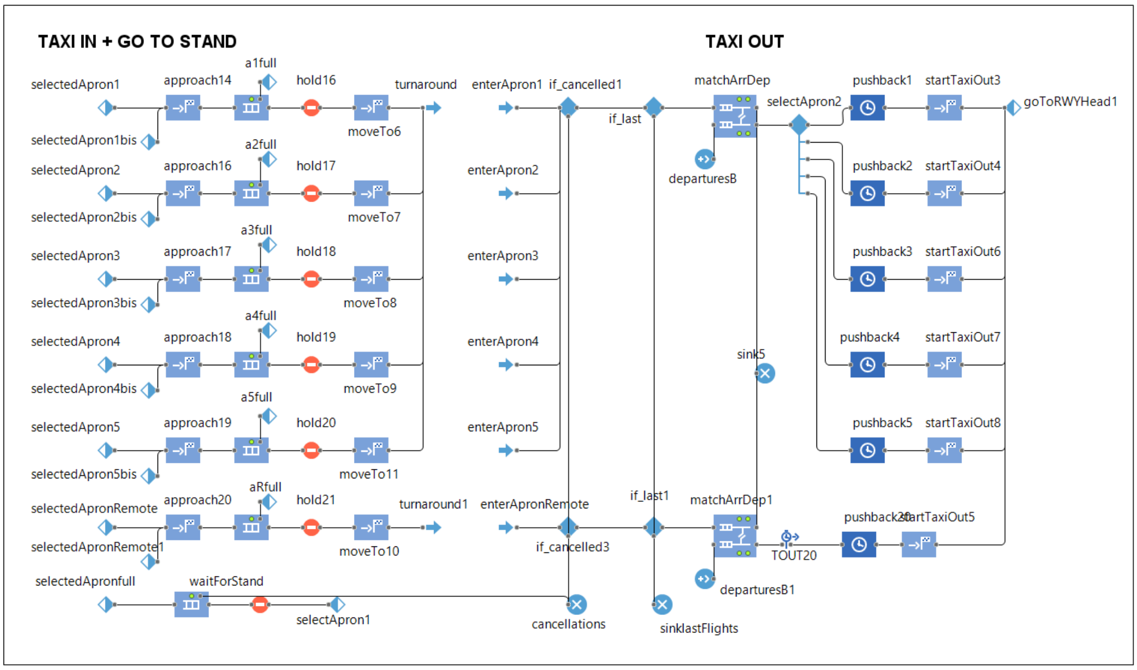
Lastly, this work paves the way for several lines of research. In fact, it might be valuable to include also passengers' processes, as they are among the most affected stakeholders in case of disruptions. In addition, the analysis may be extended to landside operations, such as check-in and security control processes, in order to obtain a comprehensive model for the entire airport. Moreover, future research could explore different indicators of resilience and vulnerability, by disaggregating the impacts on the specific stakeholders involved - namely passengers, airlines and airport operators.

APPENDIX A: AnyLogic simulation model

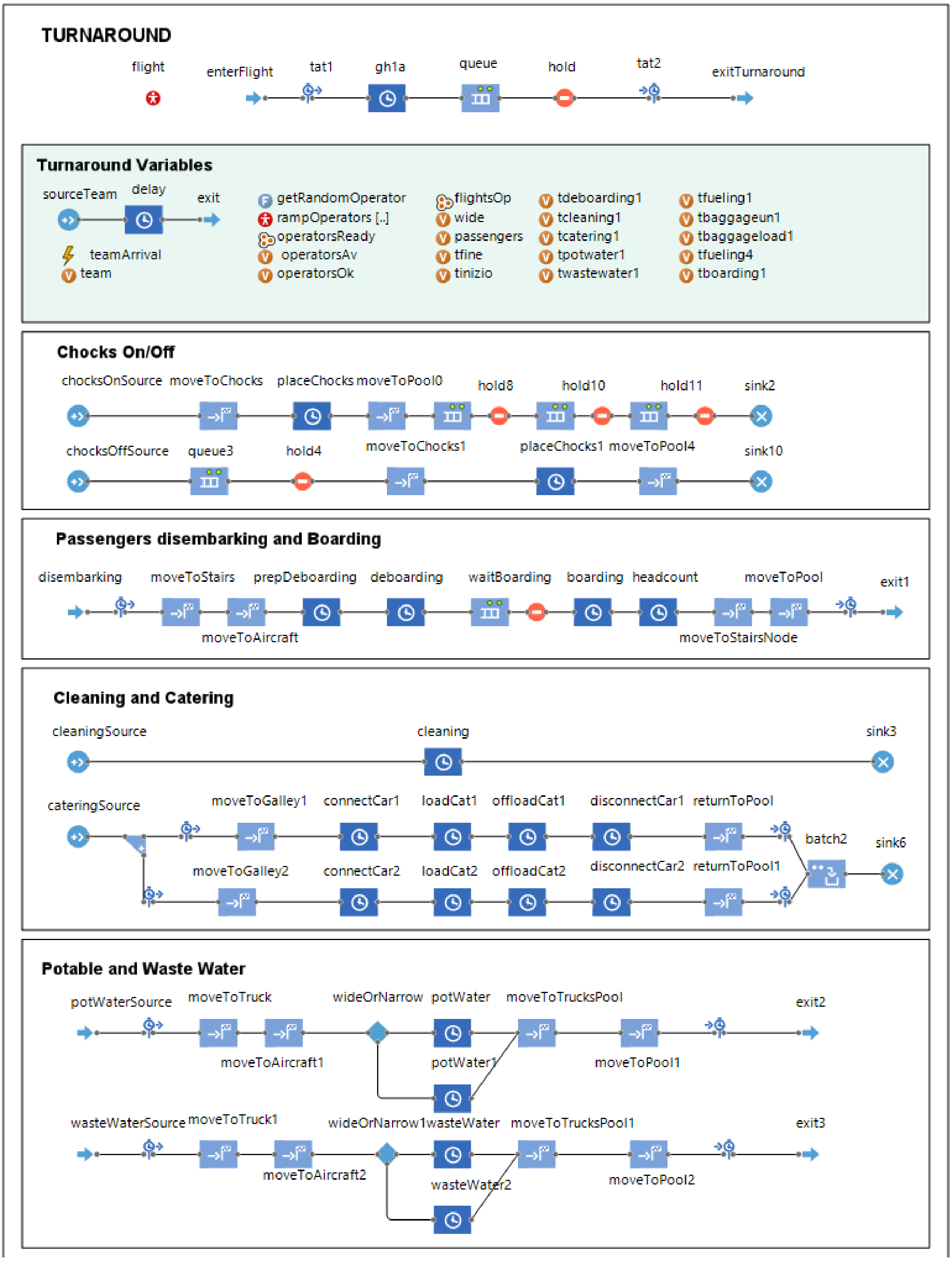


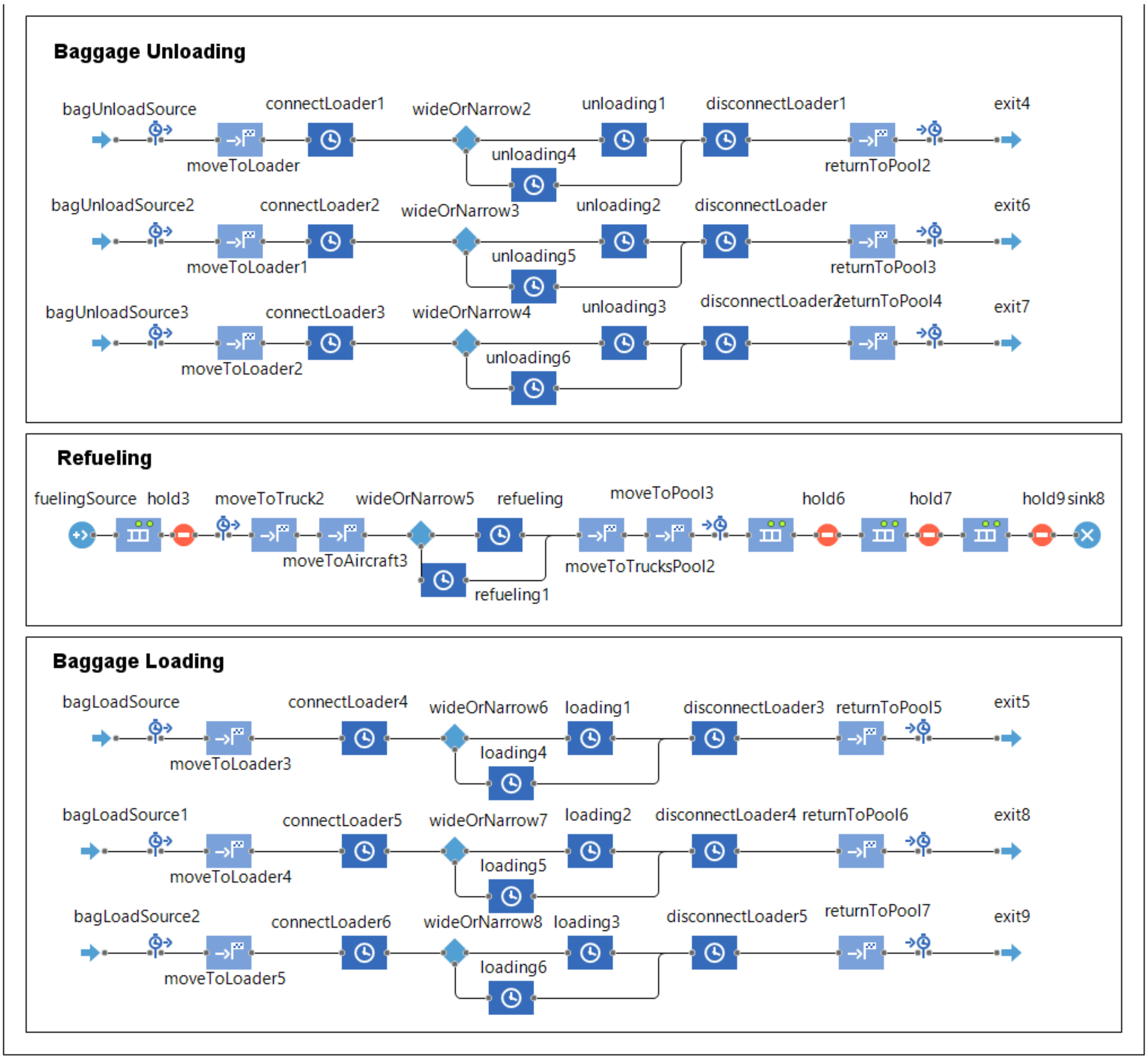



TAKE OFF
selectTakeOff1
selectRWY2
if_disruption2
selectTakeOff
selectRWY3
moveToRwyHead
moveToRwyHead1
moveToRwyHead2
moveToRwyHead3
moveToRwyHead4
hold10
hold11
hold12
hold13
hold14
if_cancelled
selectRWY4
startTakeOff
takeOff
sink
startTakeOff1
takeOff1
sink1
startTakeOff2
takeOff2
sink2
startTakeOff3
takeOff3
sink3
startTakeOff4
takeOff4
sink4
cancellations1
match1
firstDepartures
queue4
hold15
assignRWY
pushbackF
goToRWYHead
moveToNTW
TOUT70F
startTaxiOut9
firstDepartures1
sinkFirstDepartures


TAXI IN + GO TO STAND
TAXI OUT
selectApron1
approach14
a1full
hold16
turnaround
moveTo6
selectApron1bis
selectApron2
approach16
a2full
hold17
moveTo7
selectApron2bis
selectApron3
approach17
a3full
hold18
moveTo8
selectApron3bis
selectApron4
approach18
a4full
hold19
moveTo9
selectApron4bis
selectApron5
approach19
a5full
hold20
moveTo11
selectApron5bis
selectApronRemote
approach20
aRfull
hold21
turnaround1
moveTo10
selectApronRemote1
selectApronfull
waitForStand
selectApron1
enterApron1
if_cancelled1
if_last
enterApron2
enterApron3
enterApron4
enterApron5
enterApronRemote
if_cancelled3
if_last1
cancellations
sinklastFlights
matchArrDep
selectApron2
departuresB
pushback1
startTaxiOut3
goToRWYHead1
pushback2
startTaxiOut4
pushback3
startTaxiOut6
pushback4
startTaxiOut7
sink5
pushback5
startTaxiOut8
matchArrDep1
TOUT20
pushback20
startTaxiOut5
departuresB1


ARRIVALS
MOVEMENTS
DELAY_STA
DEPARTURES
TAKE OFFS
DELAY_STD
DELAY_STA_CUM
DELAY_STD_CUM


TURNAROUND
flight
enterFlight
tat1
gh1a
queue
hold
tat2
exitTurnaround
Turnaround Variables
sourceTeam
delay
exit
teamArrival
team
getRandomOperator
rampOperators [..]
operatorsReady
operatorsAv
operatorsOk
flightsOp
wide
passengers
tfine
tinizio
tdeboarding1
tcleaning1
tcatering1
tpotwater1
twastewater1
tfueling1
tbaggageun1
tbaggageload1
tfueling4
tboarding1
Chocks On/Off
chocksOnSource
moveToChocks
placeChocks
moveToPool0
hold8
hold10
hold11
sink2
chocksOffSource
queue3
hold4
moveToChocks1
placeChocks1
moveToPool4
sink10
Passengers disembarking and Boarding
disembarking
moveToStairs
prepDeboarding
deboarding
waitBoarding
boarding
headcount
moveToPool
exit1
moveToAircraft
moveToStairsNode
Cleaning and Catering
cleaningSource
cleaning
sink3
cateringSource
moveToGalley1
connectCar1
loadCat1
offloadCat1
disconnectCar1
returnToPool
batch2
sink6
moveToGalley2
connectCar2
loadCat2
offloadCat2
disconnectCar2
returnToPool1
Potable and Waste Water
potWaterSource
moveToTruck
wideOrNarrow
potWater
moveToTrucksPool
exit2
moveToAircraft1
potWater1
moveToPool1
wasteWaterSource
moveToTruck1
wideOrNarrow1
wasteWater
moveToTrucksPool1
exit3
moveToAircraft2
wasteWater2
moveToPool2



Symbol	Block name	Description
	Source	Generates agents.
	Sink	Disposes incoming agents
	Delay	Delays agents by the specified delay time
	Queue	Stores agents in the specified order.
	SelectOutput	Forwards the agent to one of the output ports depending on the condition.
	SelectOutput5	Routes the incoming agents to one of the five output ports depending on (probabilistic or deterministic) conditions

	Hold	Blocks/unblocks the agent flow.
	Match	Finds a match between two agents from different inputs, then outputs them
	Split	For each incoming agent ("original") creates one or several other agents-copies
	Combine	Waits for two agents, then produces a new agent from them
	MoveTo	Moves an agent from its current location to new location
	ResourcePool	Provides resource units that are seized and released by agents
	Enter	Inserts agents created elsewhere into the flowchart.
	Exit	Accepts incoming agents.
	TimeMeasureStart	TimeMeasureStart as well as TimeMeasureEnd compose a pair of objects measuring the time the agents spend between them, such as "time in system", "length of stay", etc. This block remembers the time when an agent goes through.
	TimeMeasureEnd	TimeMeasureEnd as well as TimeMeasureStart compose a pair of objects measuring the time the agents spend between them. For each incoming agent this object measures the time it spent since it has been through one of the corresponding TimeMeasureStart objects.
	SelectOutputIn	Both with SelectOutputOut acts as two halves of large multi-exit SelectOutput block.
	SelectOutputOut	Both with SelectOutputIn acts as two halves of large multi-exit SelectOutput block.
	Agent	Drag the Agent element from the Agent palette on the diagram of the agent type where you want to create the population of agents
	Parameter	Parameters are used for representing some characteristics of the modeled object.
	Variable	Variables are used to store the results of model simulation or to model some data units or object characteristics, changing over time
	Collection	A collection represents a group of objects, known as its elements
	Function	*Function* will return the value of an expression each time the user calls it from the model
	Event	Event is the simplest way to schedule some action in the model

APPENDIX B: Disruptions database

ID	Year	IATA Airport code	Mov/year	Runways	Capacity (mov/hour)	Aircraft stands	Ground Handlers	Disruption type	Disruption cause	Cluster	Total delay obrserved (min)	Reduced capacity (%)	Td (h)	Tr (h)	Tot delay sim (min)	Average delay (min)	Nv,r (delayed flights)	Nv,c (cancelled flights)	Nv,d (diverted flights)	Impact tot (sim)	VULNERABILITY	RESILIENCE
1	2018	AMS	498590	5	112	94	3	ATC system/communication issues	Technical_problem	A	2361	0.4	2	2.5	2383	64	37	0	15	52	20	0.041
2	2018	AMS	498590	5	112	94	3	Power issue	Technical_problem	D	6917	0	3	0.25	6532	116	56	16	111	183	99	0.121
3	2018	AMS	498590	5	112	94	3	ATC system/communication issues	Technical_problem	A	2047	0.7	9	4	2036	64	32	0	0	32	12	0.194
4	2018	AMS	498590	5	112	94	3	ATC system/communication issues	Technical_problem	A	11073	0.5	4.5	10.75	10648	85	126	0	13	139	66	0.006
5	2018	CDG	474500	4	120	301	4	ILS issues	Technical_problem	A	1492	0.4	3	1.5	1618	62	26	0	16	42	16	0.126
6	2018	BCN	310250	3	64	170	4	Aircraft on runway	Incident	B	1012	0.4	3.5	1.75	1237	54	23	0	45	68	26	0.077
7	2018	BCN	310250	3	64	170	4	Taxiway and/or apron improvements	Infrastrucural_problem	B	13892	24	20	0.5	11000	106	104	89	0	193	151	0.264
8	2018	BCN	310250	3	64	170	4	ILS issues	Technical_problem	A	3353	0.7	4	0.5	6346	60	60	0	23	83	30	0.038
9	2018	CGN	142350	3	36	110	3	Taxiway and/or apron improvements	Infrastrucural_problem	B	1198	0.7	14	1	1150	55	21	0	0	21	7	2.139
10	2018	BRU	219000	3	74	110	1	Runway maintenance/closure	Infrastrucural_problem	B	1490	0.7	10	4.75	1629	56	29	0	34	63	23	0.090
11	2018	ARN	237250	3	84	104	2	Radar issues	Technical_problem	A	1462	0.5	10	0.25	1431	55	26	0	5	31	10	3.922
12	2018	FRA	474500	3	106	221	2	ATC system/communication issues	Technical_problem	A	6276	0.7	12	0.75	6311	66	102	0	39	141	54	0.294
13	2018	LBG	54750	3	40	80	1	ILS issues	Technical_problem	A	679	0.3	9	0.25	639	58	11	0	11	22	8	4.376
14	2018	TXL	167900	2	52	50	1	Ground personnel industrial action	Industrial_action	C	1232	0.25	6	8.75	2500	77	33	164	0	197	178	0.004
15	2018	WAW	164250	2	36	100	3	Runway maintenance/closure	Infrastrucural_problem	B	1861	0.5	20	0.25	7500	103	75	15	0	90	59	1.361
16	2018	HAM	146000	2	48	54	3	Power issue	Technical_problem	D	1212	0	3	4.5	1400	75	19	6	29	54	26	0.025
17	2018	AGP	127750	2	37	98	2	Taxiway and/or apron improvements	Infrastrucural_problem	B	1478	0.5	19	0.75	1500	40	40	0	0	40	9	2.795

18	2018	LIS	200750	2	39	71	2	Radar issues	Technical_problem	A	1147	0.6	3	1	1370	65	24	0	0	24	9	0.339
19	2018	DUB	211700	2	48	62	2	Radar issues	Technical_problem	A	1040	0.2	4	1	2500	92	24	18	23	65	40	0.100
20	2018	ATH	197100	2	44	99	2	ILS issues	Technical_problem	A	1319	0.2	8	1.25	2500	68	37	32	49	118	67	0.096
21	2018	TLS	91250	2	45	65	1	Taxiway and/or apron improvements	Infrastrucural_problem	B	1447	0.4	19	0.25	1690	52	32	0	19	51	17	4.369
22	2018	MUC	365000	2	90	162	1	Evacuation	Security_related	D	1784	5.5	3	1.5	1927	96	20	26	91	137	75	0.027
23	2018	LGW	273750	2	55	146	1	Aircraft incident	Incident	B	3067	0.5	4	0.75	3139	150	21	77	0	98	95	0.056
24	2018	LGW	273750	2	55	146	1	dangerous objects	Security_related	D	4657	0	4	2.25	4600	119	39	57	62	158	109	0.016
25	2018	LGW	273750	2	55	146	1	dangerous objects	Security_related	D	5037	0	4.5	1.5	4649	113	40	65	51	156	112	0.027
26	2018	LHR	474500	2	88	197	3	Evacuation	Security_related	D	2801	0	1	2	2489	61	41	0	42	83	32	0.016
27	2018	LHR	474500	2	88	197	3	Lighting issues	Technical_problem	A	2237	0.1	7	0.25	2771	99	28	90	247	365	209	0.134
28	2018	OPO	83950	1	24	39	2	ILS issues	Technical_problem	A	4833	0.2	19	0.5	3210	78	41	3	70	114	50	0.753
29	2018	OPO	83950	1	24	39	2	ILS issues	Technical_problem	A	2096	0.2	10	7.5	2093	67	31	3	25	59	25	0.053
30	2018	GVA	146000	1	40	51	1	Aircraft on runway	Incident	B	1188	0	2	16.25	1700	95	18	13	1	32	23	0.005
31	2018	BLQ	73000	1	20	24	3	ground operations issues	Technical_problem	C	1051	0	2.5	2.25	1020	113	9	20	0	29	26	0.043
32	2018	CTA	65700	1	25	26	4	Volcanic eruption	Extreme_weather	D	1640	0	2.5	1.5	1300	130	10	0	13	23	13	0.130
33	2018	RHO	36500	1	20	13	4	ground operations issues	Technical_problem	C	1167	0.8	15	1	1230	50	25	0	0	25	7	2.118
34	2018	KGS	16425	1	10	7	1	VOR issues	Technical_problem	A	754	0.4	19	0.25	811	58	14	0	6	20	7	10.680
35	2018	PSA	36500	1	13	20	1	Fire	Security_related	D	800	0	19	0.25	700	19	63	0	19	82	15	5.153
36	2018	NTE	54750	1	20	27	3	Taxiway and/or apron improvements	Infrastrucural_problem	B	1066	0	5	1	976	109	9	0	5	14	8	0.653
37	2018	ACE	54750	1	24	30	1	VOR issues	Technical_problem	A	1123	0.4	13	1	1196	50	24	0	7	31	10	1.336
38	2018	ACE	54750	1	24	30	1	Taxiway and/or apron improvements	Infrastrucural_problem	B	700	0	2.5	5.25	778	111	12	0	7	19	10	0.045
39	2018	NTE	54750	1	20	27	3	Radar issues	Technical_problem	A	1000	0.2	10	1.25	1016	53	19	0	26	45	17	0.482
40	2018	STN	171550	1	50	110	2	Runway maintenance/closure	Infrastrucural_problem	B	1992	0	4	1	1900	135	14	22	44	80	51	0.078

41	2017	AMS	498590	5	112	94	3	Radar issues	Technical_problem	A	11406	0.6	7	2.5	10813	83	131	0	31	162	75	0.038
42	2017	AMS	498590	5	112	94	3	Aircraft incident	Incident	B	31321	0.6	7.5	10	26000	92	280	0	4	284	148	0.005
43	2017	AMS	498590	5	112	94	3	ground operations issues	Technical_problem	C	8223	1	8	8.25	7500	64	116	0	0	116	42	0.023
44	2017	AMS	498590	5	112	94	3	ILS issues	Technical_problem	A	1851	0.7	6	1.5	2001	61	33	0	0	33	11	0.351
45	2017	AMS	498590	5	112	94	3	Radar issues	Technical_problem	A	1555	0.7	5.5	9.25	1409	59	24	0	0	24	8	0.074
46	2017	AMS	498590	5	112	94	3	ATC system/communication issues	Technical_problem	A	8581	0.6	5	5.75	8429	80	105	0	12	117	53	0.017
47	2017	CDG	474500	4	120	301	4	Radar issues	Technical_problem	A	1498	0.6	9	0.75	1634	61	27	0	0	27	9	1.286
48	2017	FCO	292000	4	90	131	5	Fire	Security_related	D	1316	0	1	1	1434	59	24	0	0	24	8	0.125
49	2017	BCN	310250	3	64	170	4	ILS issues	Technical_problem	A	1096	0.7	1	7.75	1500	47	36	0	0	36	10	0.013
50	2017	BCN	310250	3	64	170	4	ILS issues	Technical_problem	A	1165	0.6	1	5.25	1332	51	26	0	0	26	8	0.025
51	2017	HEL	167900	3	80	109	4	Runway maintenance/closure	Infrastrucural_problem	B	1459	0.6	6	6.25	1500	70	22	88	0	110	97	0.010
52	2017	BRU	219000	3	74	110	1	Lighting issues	Technical_problem	A	2106	0.4	11	2.25	2119	59	36	0	11	47	17	0.294
53	2017	ORY	226300	3	76	104	4	ATC Industrial action	Industrial_action	A	3945	0.2	4	11	4072	75	54	0	23	77	33	0.011
54	2017	ORY	226300	3	76	104	4	ATC Industrial action	Industrial_action	A	4664	0.3	13	5	4491	62	72	0	58	130	50	0.052
55	2017	IST	438000	3	80	111	1	ILS issues	Technical_problem	A	2014	0.5	5	1.25	2027	55	36	0	40	135	66	0.060
56	2017	LBG	54750	3	40	80	1	ILS issues	Technical_problem	A	739	0.4	12	1	737	57	13	0	13	26	10	1.244
57	2017	LBG	54750	3	40	80	1	ILS issues	Technical_problem	A	2658	0.1	15	1.25	2288	99	23	0	67	90	41	0.293
58	2017	LBG	54750	3	40	80	1	ILS issues	Technical_problem	A	1471	0.2	15	0.25	1446	63	23	0	49	72	29	2.087
59	2017	TXL	167900	2	52	50	1	Ground personnel industrial action	Industrial_action	C	5687	0.6	6	7	6700	170	39	96	0	135	134	0.006
60	2017	TXL	167900	2	52	50	1	Ground personnel industrial action	Industrial_action	C	2568	0.25	13	4	2900	122	24	220	0	244	237	0.014
61	2017	LIS	200750	2	39	71	2	ATC system/communication issues	Technical_problem	A	5386	0.5	5	2.5	5600	84	70	1	0	71	34	0.058
62	2017	LIS	200750	2	39	71	2	ILS issues	Technical_problem	A	1115	0.7	2.5	1	1200	61	20	0	0	20	7	0.362
63	2017	DUS	211700	2	47	107	4	Aircraft on runway	Incident	B	2734	0.5	5	2	2760	77	36	0	0	36	16	0.159

64	2017	MAN	197100	2	61	94	4	Fire	Security_related	D	2056	0	3	1.75	2028	101	20	30	26	76	52	0.033
65	2017	MAN	197100	2	61	94	4	Evacuation	Security_related	D	1339	0	2	2.25	1365	85	16	14	22	52	31	0.029
66	2017	PMI	197100	2	44	96	3	Radar issues	Technical_problem	A	6177	0.4	11	0.5	6200	95	65	26	41	132	78	0.281
67	2017	BGY	83950	2	26	47	2	ATC Industrial action	Industrial_action	A	1911	0.4	6	1.25	1900	71	26	5	8	39	19	0.255
68	2017	MXP	171550	2	70	194	2	ATC Industrial action	Industrial_action	A	2302	0.4	5	1.25	2580	81	32	0	4	36	16	0.244
69	2017	BOD	54750	2	50	30	3	ATC Industrial action	Industrial_action	A	800	0.2	11	2.75	775	39	20	0	0	20	4	0.905
70	2017	BOD	54750	2	50	30	3	Power issue	Technical_problem	D	1032	0	2.5	5.75	1021	51	20	0	25	45	16	0.027
71	2017	HER	54750	2	22	14	4	VOR issues	Technical_problem	A	1876	0.4	8	0.25	1930	71	27	0	1	28	11	2.837
72	2017	LHR	474500	2	88	197	3	Aircraft on runway	Incident	B	2452	0.5	2	3.25	2651	63	42	0	41	83	32	0.019
73	2017	LHR	474500	2	88	197	3	ILS issues	Technical_problem	A	3346	0.6	2	6.25	3424	55	62	0	34	96	34	0.010
74	2017	SXF	91250	1	26	52	3	Ground personnel industrial action	Industrial_action	C	2568	0.25	13	2.25	3900	110	36	46	0	82	68	0.084
75	2017	CTA	65700	1	25	26	4	Volcanic eruption	Extreme_weather	D	1525	0	11	0.25	1527	94	57	27	0	84	57	0.767
76	2017	CTA	65700	1	25	26	4	Radar issues	Technical_problem	A	1173	0.2	8	3.25	1103	53	21	0	30	51	19	0.130
77	2017	IBZ	65700	1	28	29	2	Radar issues	Technical_problem	A	1253	0.2	10	1	1267	58	22	0	31	53	20	0.494
78	2017	CTA	65700	1	25	26	4	Radar issues	Technical_problem	A	1516	0.3	13	0.25	1499	50	30	0	28	58	20	2.569
79	2017	CTA	65700	1	25	26	4	Radar issues	Technical_problem	A	1845	0.1	15	1.75	1800	90	20	6	68	94	45	0.192
80	2017	TFS	65700	1	33	50	2	Aircraft on runway	Incident	B	1432	0	2	1	1498	94	16	0	0	16	9	0.235
81	2017	LCY	73000	1	39	18	1	ground operations issues	Technical_problem	C	5790	0.4	10.5	3	5691	114	50	5	0	55	37	0.094
82	2017	RHO	36500	1	20	13	4	Radar issues	Technical_problem	A	1008	0.1	19	0.25	983	58	17	0	23	40	15	4.990
83	2017	PSA	36500	1	13	20	1	Radar issues	Technical_problem	A	2584	0.2	19	0.25	955	80	12	0	16	28	12	6.257
84	2017	NTE	54750	1	20	27	3	Terrorism	Security_related	D	1001	0	5.5	1	1300	121	11	0	5	16	10	0.571
85	2016	CDG	474500	4	120	301	4	dangerous objects	Security_related	D	2615	0	1.5	0.5	2493	80	31	0	26	57	25	0.120
86	2016	FCO	292000	4	90	131	5	ground operations issues	Technical_problem	C	3167	0.7	9	1	3119	57	55	0	0	55	18	0.507

87	2016	ZRH	237250	3	66	100	1	Radar issues	Technical_problem	A	1024	0.6	5	1.25	1146	57	20	0	0	20	6	0.619
88	2016	FRA	474500	3	106	221	2	VOR issues	Technical_problem	A	2452	0.4	2	1	2688	62	43	0	13	56	21	0.097
89	2016	FRA	474500	3	106	221	2	VOR issues	Technical_problem	A	1295	0.6	3	1.5	1586	55	29	0	0	29	9	0.221
90	2016	FRA	474500	3	106	221	2	Evacuation	Security_related	D	2796	0	1	2.5	2699	54	50	0	10	60	19	0.021
91	2016	IST	438000	3	80	111	1	Terrorism	Security_related	D	2261	0	1	2.25	2276	54	42	0	16	58	20	0.023
92	2016	IST	438000	3	80	111	1	Radar issues	Technical_problem	A	6328	0.6	9	1	6005	63	95	0	69	164	63	0.143
93	2016	LBG	54750	3	40	80	1	ILS issues	Technical_problem	A	1654	0.2	15	1	1741	67	26	0	46	72	29	0.514
94	2016	LBG	54750	3	40	80	1	ILS issues	Technical_problem	A	2830	0.3	10	1.25	953	60	16	0	13	29	11	0.735
95	2016	TXL	167900	2	52	50	1	ground operations issues	Technical_problem	C	6483	1	2.5	10.75	3000	94	32	40	0	72	57	0.004
96	2016	WAW	164250	2	40	100	3	Lighting issues	Technical_problem	A	1143	0.5	3	5.25	1100	59	18	0	0	18	6	0.095
97	2016	LIS	200750	2	39	71	2	Runway maintenance/closure	Infrastrucural_problem	B	1352	1	10	8.25	1500	58	26	0	0	26	9	0.142
98	2016	MAN	197100	2	61	94	4	Aircraft on runway	Incident	B	1228	0.5	3	3.25	1264	58	22	0	0	22	7	0.128
99	2016	MRS	91250	2	30	55	2	Fire	Security_related	D	3762	0	2	5	1800	91	20	6	0	26	16	0.025
100	2016	LGW	273750	2	55	146	1	Runway contamination	Incident	B	6235	0.5	13	0.5	6115	157	39	300	0	339	335	0.078
101	2016	LGW	273750	2	55	146	1	Runway maintenance/closure	Infrastrucural_problem	B	4040	0.5	3	3.5	4721	127	37	52	0	89	79	0.011
102	2016	LGW	273750	2	55	146	1	ground operations issues	Technical_problem	C	4203	0.6	13	2.25	4297	52	83	0	0	83	24	0.236
103	2016	VIE	219000	2	68	99	1	ATC system/communication issues	Technical_problem	A	2523	0.4	4	2.25	2543	64	40	0	13	53	20	0.089
104	2016	OSL	240900	2	80	71	2	ATC system/communication issues	Technical_problem	A	1248	0.4	2	1.25	1289	68	19	0	0	19	7	0.219
105	2016	LHR	474500	2	88	197	3	Emergency landing	Incident	A	1485	0.5	2	3	1488	62	24	0	39	63	25	0.027
106	2016	CTA	65700	1	25	26	4	Radar issues	Technical_problem	A	1644	0.3	12	0.25	1677	62	27	0	32	59	23	2.096
107	2016	LCY	73000	1	39	18	1	ground operations issues	Technical_problem	C	2041	0.3	12	1.75	1957	56	35	0	0	35	11	0.617
108	2016	LCY	73000	1	39	18	1	Lighting issues	Technical_problem	A	2182	0.1	12	1.25	2175	87	25	1	40	66	30	0.319
109	2016	CIA	36500	1	20	82	3	Ground personnel industrial action	Industrial_action	C	1352	0.5	8	1.5	1385	73	19	0	0	19	8	0.679

110	2016	PSA	36500	1	13	20	1	Radar issues	Technical_problem	A	1090	0.2	15	4.25	800	80	10	0	14	24	10	0.339
111	2016	CAG	31025	1	14	16	1	Radar issues	Technical_problem	A	1209	0.2	19	0.25	983	58	17	0	23	40	15	4.990
112	2016	NTE	54750	1	20	27	3	Radar issues	Technical_problem	A	450	0.3	8	4.75	546	45	12	0	10	22	7	0.232
113	2016	SAW	208050	1	40	136	1	Radar issues	Technical_problem	A	6328	0.3	15	2	6203	105	59	18	51	128	74	0.101
114	2015	AMS	498590	5	112	94	3	Taxiway and/or apron improvements	Infrastrucural_problem	B	2640	1	2	3	2400	60	40	0	0	40	14	0.049
115	2015	AMS	498590	5	112	94	3	Snow	Extreme_weather	A	3362	0.6	4.5	5	3653	66	55	0	4	59	22	0.040
116	2015	AMS	498590	5	112	94	3	ATC system/communication issues	Technical_problem	A	2369	0.4	2	2.5	2383	64	37	0	15	52	20	0.041
117	2015	AMS	498590	5	112	94	3	Power issue	Technical_problem	D	5428	0	2.5	2.75	5984	109	55	0	103	158	77	0.012
118	2015	CDG	474500	4	120	301	4	Security incident	Incident	B	2768	0.7	4.5	1.5	2893	83	35	0	0	35	16	0.182
119	2015	CDG	474500	4	120	301	4	Ground personnel industrial action	Industrial_action	C	5852	0.3	8	1.75	5606	59	95	0	0	95	32	0.144
120	2015	FCO	292000	4	90	131	5	Fire	Security_related	A	9156	0.2	15	1	8588	97	89	9	269	367	171	-0.005
121	2015	FCO	292000	4	90	131	5	Fire	Security_related	D	2449	0	2.5	1.25	2630	120	22	0	56	78	38	0.052
122	2015	AYT	149650	3	60	92	1	Runway maintenance/closure	Infrastrucural_problem	B	5126	0.7	19	0.5	5700	102	57	22	0	79	55	0.692
123	2015	AYT	149650	3	60	92	1	Runway maintenance/closure	Infrastrucural_problem	B	2935	0.7	11	0.25	3100	82	38	24	0	62	42	1.056
124	2015	AYT	149650	3	60	92	1	Runway maintenance/closure	Infrastrucural_problem	B	6157	0.5	13	3.25	6500	91	72	47	4	123	86	0.047
125	2015	ORY	226300	3	76	104	4	Runway maintenance/closure	Infrastrucural_problem	B	768	0.7	18	0.25	795	53	15	0	17	32	12	6.190
126	2015	ZRH	237250	3	66	100	1	ILS issues	Technical_problem	A	2285	0.4	5	3.25	2138	58	37	0	25	62	23	0.068
127	2015	FRA	474500	3	106	221	2	ground operations issues	Technical_problem	C	5196	0.7	8	1.5	5146	52	98	0	0	98	29	0.185
128	2015	IST	438000	3	80	111	1	Aircrft incident	Incident	B	4035	0.6	16	0.25	4283	56	77	0	78	155	57	1.120
129	2015	IST	438000	3	80	111	1	ATC system/communication issues	Technical_problem	A	3646	0.5	4	2.25	3468	63	55	0	30	85	32	0.055
130	2015	DUB	211700	2	48	62	2	Fire	Security_related	D	3407	0	1.5	2.5	3749	71	52	1	14	67	28	0.022
131	2015	LGW	273750	2	55	146	1	Thunderstorm	Extreme_weather	C	13777	0.2	16	0.75	13210	75	146	0	0	146	62	0.344
132	2015	LHR	474500	2	88	197	3	Security incident	Incident	B	12647	0.5	6	2.75	10659	82	130	0	201	331	145	0.015

133	201 5	PSA	36500	1	13	20	1	ILS issues	Technical_problem	A	2444	0.2	19	0.25	1000	77	13	0	14	27	12	6.585
134	201 5	SAW	20805 0	1	40	136	1	ATC system/communication issues	Technical_problem	A	5488	0.3	12	1.25	5564	124	45	18	46	109	69	0.139
135	201 5	SAW	20805 0	1	40	136	1	Thunderstorm	Extreme_weather	A	1377 1	0.3	14	1.5	1053 4	116	91	9	55	155	92	0.102

REFERENCES

Adeleye, S., & Chung, C. (2006). A simulation based approach for contingency planning for aircraft turnaround operation system activities in airline hubs. Journal of Air Transportation (Vol. 11). Retrieved from https://ntrs.nasa.gov/search.jsp?R=20060053395

Adjetey-Bahun, K., Birregah, B., Châtelet, E., & Planchet, J. L. (2016). A model to quantify the resilience of mass railway transportation systems. Reliability Engineering and System Safety, 153, 1–14. https://doi.org/10.1016/j.ress.2016.03.015

Agrawal, S., Agrawal, D., Chen, C. B., Hutchison, K., & Kumara, S. (2015). Robustness analysis of Indian Airport Network: A graph analysis approach. In IIE Annual Conference and Expo 2015 (pp. 1524–1532).

AIRBUS, S. A. S., 2017. Aircraft characteristics-airport and maintenance planning. In: Airbus A380, Rev: May 01/17.

Alderson, D. L., & Doyle, J. C. (2010). Contrasting Views of Complexity and Their Implications For Network-Centric Infrastructures. IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, 40(4), 839–852. https://doi.org/10.1109/TSMCA.2010.2048027

Asgary, A., Nosedal, J., Solis, A. O., Longo, F., Alessio, L. E., & Curinga, M. C. (2016). Simulating the impacts of airport closures on airline route networks. In 18th International Conference on Harbor, Maritime and Multimodal Logistics Modelling and Simulation, HMS 2016 (pp. 86–92).

Ashford, N. J., Mumayiz, S., & Wright, P. H. (2011). Airport engineering: planning, design, and development of 21st century airports. John Wiley & Sons.

Ashford, N.J., Stanton, H.P.M, & Moore, C.A. (2013). Airport operations. 3rd Ed., McGraw-Hill, New York, NY, USA.

ASME (American Society of Mechanical Engineers), (2009). All Hazards Risk and Resilience–Prioritizing Critical Infrastructure Using the RAMCAP Plus SM Approach. ASME Innovative Technology Institute, Washington, DC.

Aven, T. (2011). On Some Recent Definitions and Analysis Frameworks for Risk, Vulnerability, and Resilience. Risk Analysis, 31(4), 515–522. https://doi.org/10.1111/j.1539-6924.2010.01528.x

Aydin, N. Y., Duzgun, H. S., Wenzel, F., & Heinimann, H. R. (2018). Integration of stress testing with graph theory to assess the resilience of urban road networks under seismic hazards. Natural Hazards, 91(1), 37–68. https://doi.org/10.1007/s11069-017-3112-z

Baroud, H., Ramirez-Marquez, J. E., Barker, K., & Rocco, C. M. (2014). Stochastic Measures of Network Resilience: Applications to Waterway Commodity Flows. Risk Analysis, 34(7), 1317–1335. https://doi.org/10.1111/risa.12175

Beiler, M., McNeil, S., Ames, D., & Gayley, R. (2013). Identifying resiliency performance measures for megaregional planning. Transportation Research Record, (2397), 153–160. https://doi.org/10.3141/2397-18

Belkoura, S., Peña, J. M., & Zanin, M. (2016). Generation and recovery of airborne delays in air transport. Transportation Research Part C, 69, 436–450. https://doi.org/10.1016/j.trc.2016.06.018

Berche, B., Von Ferber, C., Holovatch, T., & Holovatch, Y. (2009). Resilience of public transport networks against attacks. The European Physical Journal B, 71(1), 125-137. https://doi.org/10.1140/epjb/e2009-00291-3

Berdica, K. (2002). An introduction to road vulnerability: What has been done, is done and should be done. Transport Policy, 9(2), 117–127. https://doi.org/10.1016/S0967-070X(02)00011-2

Bevilacqua, M., Ciarapica, F. E., Mazzuto, G., & Paciarotti, C. (2015). The impact of business growth in the operation activities: a case study of aircraft ground handling operations. Production Planning & Control, 26(7), 564–587. https://doi.org/10.1080/09537287.2014.939234

Billinton, R., & Allan, R. N. (1983). Reliability Evaluation of Engineering Systems. Boston, MA: Springer US. https://doi.org/10.1007/978-1-4615-7728-7

Bocchini, P., Frangopol, D. M., Ummenhofer, T., & Zinke, T. (2014). Resilience and sustainability of civil infrastructure: Toward a unified approach. Journal of Infrastructure Systems, 20(2). https://doi.org/10.1061/(ASCE)IS.1943-555X.0000177

Brand, F. S., & Jax, K. (2007). Focusing the Meaning(s) of Resilience: Resilience as a Descriptive Concept and a Boundary Object. Ecology and Society, 12(1), art23. https://doi.org/10.5751/ES-02029-120123

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O’Rourke, T. D., Reinhorn, A. M., Shinozuka, M., Tierney, K., Wallace, W.A., & von Winterfeldt, D. (2003). A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities. Earthquake Spectra, 19(4), 733–752. https://doi.org/10.1193/1.1623497

Bubalo, B., & Daduna, J. R. (2011). Airport capacity and demand calculations by simulation—the case of Berlin-Brandenburg International Airport. NETNOMICS: Economic Research and Electronic Networking, 12(3), 161-181.

Bujor, A., & Ranieri, A. (2016). Assessing Air Traffic Management Performance Interdependencies through Bayesian Networks: Preliminary Applications and Results. Journal of Traffic and Transportation Engineering, 4, 34–48. https://doi.org/10.17265/2328-2142/2016.01.005

Cardillo, A., Zanin, M., Gómez-Gardeñes, J., Romance, M., García del Amo, A. J., & Boccaletti, S. (2013). Modeling the multi-layer nature of the European Air Transport Network: Resilience and passengers re-scheduling under random failures. European Physical Journal: Special Topics, 215(1), 23–33. https://doi.org/10.1140/epjst/e2013-01712-8

Cats, O., Yap, M., & van Oort, N. (2016). Exposing the role of exposure: Public transport network risk analysis. Transportation Research Part A: Policy and Practice, 88, 1–14. https://doi.org/10.1016/j.tra.2016.03.015

Cerqueti, R., Ferraro, G., & Iovanella, A. (2019). Measuring network resilience through connection patterns. Reliability Engineering and System Safety, 188, 320–329. https://doi.org/10.1016/j.ress.2019.03.030

Chandramouleeswaran, K. R., & Tran, H. T. (2018). Data-driven resilience quantification of the US Air transportation network. In 12th Annual IEEE International Systems Conference, SysCon 2018 - Proceedings (pp. 1–7). https://doi.org/10.1109/SYSCON.2018.8369602

Chang, S. E., & Shinozuka, M. (2004). Measuring improvements in the disaster resilience of communities. Earthquake Spectra, 20(3), 739–755. https://doi.org/10.1193/1.1775796

Chen, B., Hong, J., & Wang, Y. (1997). The minimum feature subset selection problem. Journal of Computer Science and Technology, 12(2). https://doi.org/10.1007/bf02951333

Chen, L., & Miller-Hooks, E. (2012). Resilience: An indicator of recovery capability in intermodal freight transport. Transportation Science, 46(1), 109–123. https://doi.org/10.1287/trsc.1110.0376

Chen, X., Li, J. H., & Gao, Q. (2015). A simple process simulation model for strategic planning on the airside of an airport: A case study. Journal of Simulation, 9(1), 64–72. https://doi.org/10.1057/jos.2014.20

Cheng, Y. (1998). Solving push-out conflicts in apron taxiways of airports by a network-based simulation. Computers & industrial engineering, 34(2), 351-369.

Clark, K. L., Bhatia, U., Kodra, E. A., & Ganguly, A. R. (2018). Resilience of the U.S. National airspace system airport network. IEEE Transactions on Intelligent Transportation Systems, 19(12), 3785–3794. https://doi.org/10.1109/TITS.2017.2784391

Colvin, H. M., & Taylor, R. M. (2012). Building a Resilient Workforce: Opportunities for the Department of Homeland Security: Workshop Summary. National Academies Press, Washington DC.

Cook, A., Blom, H. A. P., Lillo, F., Mantegna, R. N., Miccichè, S., Rivas, D., Vàsquez, R., & Zanin, M. (2015). Applying complexity science to air traffic management. Journal of Air Transport Management, 42, 149–158. https://doi.org/10.1016/j.jairtraman.2014.09.011

Cook, A., Delgado, L., Tanner, G., & Cristóbal, S. (2016). Measuring the cost of resilience. Journal of Air Transport Management, 56(Part A), 38–47. https://doi.org/10.1016/j.jairtraman.2016.02.007

Cook, A., & Tanner, G. (2015). European airline delay cost reference values. Final Report. University of Westminster for EUROCONTROL Performance Review Unit.

Cook, A., Tanner, G., & Anderson, S. (2004). Evaluating the true cost to airlines of one minute of airborne or ground delay: final report. Retrieved from http://eprints.wmin.ac.uk

Cook, A., Tanner, G., Williams, V., & Meise, G. (2009). Dynamic cost indexing - Managing airline delay costs. Journal of Air Transport Management, 15(1), 26–35. https://doi.org/10.1016/j.jairtraman.2008.07.001

Cooper, G. F., & Herskovits, E. (1992). A Bayesian method for the induction of probabilistic networks from data. Machine Learning, 9(4), 309–347. https://doi.org/10.1007/BF00994110

Cutter, S. L., Emrich, C. T., Webb, J. J., & Morath, D. (2009). Social vulnerability to climate variability hazards: A review of the literature. Final Report to Oxfam America, 5, 1-44.

D'Lima, M., & Medda, F. (2015). A new measure of resilience: An application to the London Underground. Transportation Research Part A: Policy and Practice, 81, 35–46. https://doi.org/10.1016/j.tra.2015.05.017

Damgacioglu, H., Celik, N., & Guller, A. (2018). A route-based network simulation framework for airport ground system disruptions. Computers and Industrial Engineering, 124, 449–461. https://doi.org/10.1016/j.cie.2018.07.029

Dawid, A. P. (1992). Applications of a general propagation algorithm for probabilistic expert systems. Statistics and Computing, 2(1), 25–36. https://doi.org/10.1007/BF01890546

De Oña, J., Mujalli, R. O., & Calvo, F. J. (2011). Analysis of traffic accident injury severity on Spanish rural highways using Bayesian networks. Accident Analysis and Prevention, 43(1), 402–411. https://doi.org/10.1016/j.aap.2010.09.010

Deary, D. S., Walker, K. E., & Woods, D. D. (2013). Resilience in the Face of a Superstorm. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 57(1), 329–333. https://doi.org/10.1177/1541931213571072

Dent, R. J., & Cameron, R. J. S. (2003). Developing Resilience in Children Who are in Public Care: The educational psychology perspective. Educational Psychology in Practice, 19(1), 3–19. https://doi.org/10.1080/0266736032000061170

De Neufville, R., & Odoni, A. (2003). Airport Systems: Planning, Design, and Management. McGraw-Hill, NewYork, NY, USA.

DHS (Department of Homeland Security), (2006). National infrastructure protection plan. Office of the Secretary of Homeland Security, Washington, DC.

Doyle, J. C., & Csete, M. (2011). Architecture, constraints, and behavior. Proceedings of the National Academy of Sciences, 108(Supplement 3), 15624-15630.

Dunn, S., & Wilkinson, S. M. (2016). Increasing the resilience of air traffic networks using a network graph theory approach. Transportation Research Part E: Logistics and Transportation Review, 90, 39–50. https://doi.org/10.1016/j.tre.2015.09.011

Enjalbert, S., & Vanderhaegen, F. (2017). A hybrid reinforced learning system to estimate resilience indicators. Engineering Applications of Artificial Intelligence, 64, 295–301. https://doi.org/10.1016/j.engappai.2017.06.022

EU (European Commission). (2018). Critical Infrastructures. Retrieved from https://ec.europa.eu/home-affairs/what-we-do/policies/crisis-and-terrorism/critical-infrastructure_en. (14 March 2018).

Eurocontrol (2013). ATFCM Users Manual. Edition 17.0. European Organisation for the Safety of Air Navigation, Brussels.

Eurocontrol (2015). Annual Network Operations Report 2015. The European Organisation for the Safety of Air Navigation, Brussels.

Eurocontrol (2016). Annual Network Operations Report 2016. The European Organisation for the Safety of Air Navigation, Brussels.

Eurocontrol (2016). ACAM (Airport Capacity Assessment Methodolgy) Manual. The European Organisation for the Safety of Air Navigation, Brussels.

Eurocontrol (2017). Annual Network Operations Report 2017. The European Organisation for the Safety of Air Navigation, Brussels.

Eurocontrol (2018). Annual Network Operations Report 2018. The European Organisation for the Safety of Air Navigation, Brussels.

Eurocontrol (2018b). Standard Inputs for EUROCONTROL Cost-Benefit Analyses. The European Organisation for the Safety of Air Navigation, Brussels.

Eurocontrol (2018c). Performance Review Report 2018. The European Organisation for the Safety of Air Navigation, Brussels.

Eurocontrol (2019). Annnual Network Operations Report 2019. The European Organisation for the Safety of Air Navigation, Brussels.

Eurocontrol (2019b). Top Stats December 2019. The European Organisation for the Safety of Air Navigation, Brussels.

Farhadi, N., Parr, S. A., Mitchell, K. N., & Wolshon, B. (2016). Use of nationwide automatic identification system data to quantify resiliency of marine transportation systems. Transportation Research Record, 2549, 9–18. https://doi.org/10.3141/2549-02

Faturechi, R., Levenberg, E., & Miller-Hooks, E. (2014). Evaluating and optimizing resilience of airport pavement networks. Computers & Operations Research, 43, 335-348. https://doi.org/10.1016/j.cor.2013.10.009

Faturechi, R., & Miller-Hooks, E. (2014). Travel time resilience of roadway networks under disaster. Transportation Research Part B: Methodological, 70, 47–64. https://doi.org/10.1016/j.trb.2014.08.007

Faturechi, R., & Miller-Hooks, E. (2015). Measuring the performance of transportation infrastructure systems in disasters: A comprehensive review. Journal of infrastructure systems, 21(1). https://doi.org/10.1061/(ASCE)IS.1943-555X.0000212

Filippone, E., Gargiulo, F., Errico, A., Di Vito, V., & Pascarella, D. (2016). Resilience management problem in ATM systems as a shortest path problem. Journal of Air Transport Management, 56(Part A), 57–65. https://doi.org/10.1016/j.jairtraman.2016.03.014

Finkel, M., & Tlamim, M. (2011). On flexibility: recovery from technological and doctrinal surprise on the battlefield. Stanford University Press, CA.

Francis, R., & Bekera, B. (2014). A metric and frameworks for resilience analysis of engineered and infrastructure systems. Reliability Engineering and System Safety. https://doi.org/10.1016/j.ress.2013.07.004

Freckleton, D., Heaslip, K., Louisell, W., & Collura, J. (2012). Evaluation of resiliency of transportation networks after disasters. Transportation Research Record, (2284), 109–116. https://doi.org/10.3141/2284-13

Friedman, N., Geiger, D., Provan, G., Langley, P., & Smyth, P. (1997). Bayesian Network Classifiers. (Vol. 29). Kluwer Academic Publishers.

Fung, R., & Chang, K. C. (1990). Weighing and Integrating Evidence for Stochastic Simulation in Bayesian Networks. In Machine Intelligence and Pattern Recognition (Vol. 10, pp. 209–219). https://doi.org/10.1016/B978-0-444-88738-2.50023-3

Fung, R., & Favero, B. Del. (1994). Backward Simulation in Bayesian Networks. In Uncertainty Proceedings 1994 (pp. 227–234). Elsevier. https://doi.org/10.1016/b978-1-55860-332-5.50034-1

Gluchshenko, O. (2012). Definitions of Disturbance, Resilience and Robustness in ATM Context. DLR Report IB 112-2012/28.

Gluchshenko, O., & Foerster, P. (2013). Performance based approach to investigate resilience and robustness of an ATM System. In Proceedings of the 10th USA/Europe Air Traffic Management Research and Development Seminar, ATM 2013.

Gregoriades, A., & Mouskos, K. C. (2013). Black spots identification through a Bayesian Networks quantification of accident risk index. Transportation Research Part C: Emerging Technologies, 28, 28–43. https://doi.org/10.1016/j.trc.2012.12.008

Grigoriev, I. I. (2017). Anylogic for three days: a practical guide. Retrieved from: https://www.anylogic.com/blog/anylogic-7-in-three-days-paperback-edition-available/

Gunderson, L. H. (2000). Ecological Resilience. In Theory and Application. Annual Review of Ecology and Systematics, 31(1), 425–439. https://doi.org/10.1146/annurev.ecolsys.31.1.425

Habrant, J. (1999). Structure learning of bayesian networks from databases by genetic algorithms-application to time series prediction in finance. IN ICEIS, 225--231. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.408.4703

Haimes, Y. Y. (2009). On the definition of resilience in systems. Risk Analysis: An International Journal, 29(4), 498-501.

Haimes, Y. Y., Crowther, K., & Horowitz, B. M. (2008). Homeland security preparedness: Balancing protection with resilience in emergent systems. Systems Engineering, 11(4), 287–308. https://doi.org/10.1002/sys.20101

Hájek, A. (2012). A philosopher's guide to probability. In Uncertainty and Risk (pp. 109-122). Routledge. https://doi.org/10.4324/9781849773607-16

Hassler, U., & Kohler, N. (2014). Resilience in the built environment. Building Research and Information. https://doi.org/10.1080/09613218.2014.873593

Henrion, M. (1988). Propagating Uncertainty in Bayesian Networks by Probabilistic Logic Sampling. In Machine Intelligence and Pattern Recognition (Vol. 5, pp. 149–163). https://doi.org/10.1016/B978-0-444-70396-5.50019-4

Henrion, M. (1990). An Introduction to Algorithms for Inference in Belief Nets. In Machine Intelligence and Pattern Recognition (Vol. 10, pp. 129–138). https://doi.org/10.1016/B978-0-444-88738-2.50017-8

Henry, D., & Emmanuel Ramirez-Marquez, J. (2012). Generic metrics and quantitative approaches for system resilience as a function of time. Reliability Engineering and System Safety. https://doi.org/10.1016/j.ress.2011.09.002

Hoffman, R. M. (1948). A Generalized Concept of Resilience. Textile Research Journal, 18(3), 141–148. https://doi.org/10.1177/004051754801800301

Holling, C.S. (1996a). Engineering Resilience versus Ecological Resilience. In Engineering within ecological constraints. Ed. Schulze, P. (pp. 31–44). National Academy Press, Washington DC, pp. 31–44.

Holling, C.S. (1996b). Surprise for Science, Resilience for Ecosystems, and Incentives for People. Ecological Applications, 6(3), 733–735. https://doi.org/10.2307/2269475

Holling, C.S. (1985). Resilience of ecosystems: local surprise and global change. In Global Change. Eds. Roederer, J.G. & Malone, T.F. (pp. 228–269). Cambridge University Press, Cambridge. Retrieved from http://pure.iiasa.ac.at/id/eprint/13667/

Holling, C. S. (1973). Resilience and Stability of Ecological Systems. Annual Review of Ecology and Systematics, 4(1), 1–23. https://doi.org/10.1146/annurev.es.04.110173.000245

Hollnagel, E. (2016). The four cornerstones of resilience engineering. In Resilience Engineering Perspectives, Volume 2, pp. 139-156. CRC Press, USA. https://doi.org/10.1201/9781315244389-17

Hollnagel, E. (2011). Prologue: the scope of resilience engineering. In Resilience engineering in practice: A guidebook, pp. xxix-xxxix. Ashgate, UK.

Hollnagel, E., Woods, D. D., & Leveson, N. (2006). Resilience engineering: concepts and precepts. Ashgate, UK.

Holme, P., Kim, B. J., Yoon, C. N., & Han, S. K. (2002). Attack vulnerability of complex networks. Physical Review E - Statistical Physics, Plasmas, Fluids, and Related Interdisciplinary Topics, 65(5), 14. https://doi.org/10.1103/PhysRevE.65.056109

Holmes, D. E., & Jain, L. C. (2008). Introduction to Bayesian networks. In Innovations in Bayesian Networks (pp. 1-5). Springer, Berlin, Heidelberg.

Hossain, M., Alam, S., Rees, T., & Abbass, H. (2013). Australian airport network robustness analysis: a complex network approach. In Proceeding of the 36th Australasian Transport Research Forum, Brisbane, Australia.

Hossain, N. U. I., Jaradat, R., Hosseini, S., Marufuzzaman, M., & Buchanan, R. K. (2019). A framework for modeling and assessing system resilience using a Bayesian network: A case study of an interdependent electrical infrastructure system. International Journal of Critical Infrastructure Protection, 25, 62–83. https://doi.org/10.1016/j.ijcip.2019.02.002

Hosseini, S., & Barker, K. (2016). Modeling infrastructure resilience using Bayesian networks: A case study of inland waterway ports. Computers and Industrial Engineering, 93, 252–266. https://doi.org/10.1016/j.cie.2016.01.007

Hosseini, S., Barker, K., & Ramirez-Marquez, J. E. (2016). A review of definitions and measures of system resilience. Reliability Engineering & System Safety, 145, 47-61. https://doi.org/10.1016/j.ress.2015.08.006

Hua, W., & Ong, G. P. (2017). Network survivability and recoverability in urban rail transit systems under disruption. IET Intelligent Transport Systems, 11(10), 641–648. https://doi.org/10.1049/iet-its.2017.0102

Huang, C., & Darwiche, A. (1996). Inference in belief networks: A procedural guide. International journal of approximate reasoning, 15(3), 225-263.

IATA (International Air Transport Association), 2008. Airport Handling Manual (AHM) −29th Edition. International Air Transport Association, Montréal.

ICAO (International Civil Aviation Organization), 2010. Volcanic Ash Contingency Plan, European and North Atlantic Regions. EUR Doc. 019, NAT Doc. 006, Part II, International Civil Aviation Organization, Paris.

ICAO (International Civil Aviation Organization), (2007). Procedures for Air Navigation Services - Air Traffic Management (PANS-ATM). ICAO Doc 4444 (up to and including amendment 4). International Civil Aviation Organization, Paris.

ICAO (International Civil Aviation Organization), (2018). Presentation of Air Transport Statistical Results. International Civil Aviation Organization, Paris. Retrieved from https://www.icao.int.

Janić. (2005). Modeling the large scale disruptions of an airline network. Journal of Transportation Engineering, 131(4), 249–260. https://doi.org/10.1061/(ASCE)0733-947X(2005)131:4(249)

Janić, M. (2015). Modelling the resilience, friability and costs of an air transport network affected by a large-scale disruptive event. Transportation Research Part A: Policy and Practice, 71, 1–16. https://doi.org/10.1016/j.tra.2014.10.023

Janić, M. (2018). Modelling the resilience of rail passenger transport networks affected by large-scale disruptive events: the case of HSR (high speed rail). Transportation, 45(4), 1101–1137. https://doi.org/10.1007/s11116-018-9875-6

Janić, M. (2019). Modeling the resilience of an airline cargo transport network affected by a large scale disruptive event. Transportation Research Part D: Transport and Environment, 77, 425-448. https://doi.org/10.1016/j.trd.2019.02.011

Jenelius, E., & Mattsson, L. G. (2012). Road network vulnerability analysis of area-covering disruptions: A grid-based approach with case study. Transportation Research Part A: Policy and Practice, 46(5), 746–760. https://doi.org/10.1016/j.tra.2012.02.003

Jin, J. G., Tang, L. C., Sun, L., & Lee, D. H. (2014). Enhancing metro network resilience via localized integration with bus services. Transportation Research Part E: Logistics and Transportation Review, 63, 17–30. https://doi.org/10.1016/j.tre.2014.01.002

Kabir, G., Tesfamariam, S., Francisque, A., & Sadiq, R. (2015). Evaluating risk of water mains failure using a Bayesian belief network model. European Journal of Operational Research, 240(1), 220-234.

Khammash, L., Mantecchini, L., & Reis, V. (2017). Micro-simulation of airport taxiing procedures to improve operation sustainability: Application of semi-robotic towing tractor. In 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems, MT-ITS 2017 - Proceedings (pp. 616–621). Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/MTITS.2017.8005587

Kim, S., & Yoon, Y. (2019). On node criticality of the Northeast Asian air route network. Journal of Air Transport Management, 80. https://doi.org/10.1016/j.jairtraman.2019.101693

Kjaerulff, U. B., & Madsen, A. L. (2008). Bayesian networks and influence diagrams. *Springer Science+ Business Media*, *200*, 114.

Klophaus, R., & Lordan, O. (2018). Codesharing network vulnerability of global airline alliances. Transportation Research Part A: Policy and Practice, 111, 1–10. https://doi.org/10.1016/j.tra.2018.02.010

Laskey, K. B., Xu, N., & Chen, C. H. (2006). Propagation of delays in the national airspace system. In Proceedings of the 22nd Conference on Uncertainty in Artificial Intelligence, UAI 2006 (pp. 265–272).

Latora, V., & Marchiori, M. (2001). Efficient behavior of small-world networks. Physical Review Letters, 87(19), 198701-1-198701–4. https://doi.org/10.1103/PhysRevLett.87.198701

Lauritzen, S. L. (1995). The EM algorithm for graphical association models with missing data. Computational Statistics and Data Analysis, 19(2), 191–201. https://doi.org/10.1016/0167-9473(93)E0056-A

Lauritzen, S. L., & Spiegelhalter, D. J. (1988). Local Computations with Probabilities on Graphical Structures and Their Application to Expert Systems. Journal of the Royal Statistical Society: Series B (Methodological), 50(2), 157–194. https://doi.org/10.1111/j.2517-6161.1988.tb01721.x

Li, B.-J., Du, W.-B., Liu, C., & Cai, K.-Q. (2014). Topologic and dynamic resilience model of Chinese airport network. In IEEE International Conference on Control and Automation, ICCA (pp. 1460–1465). https://doi.org/10.1109/ICCA.2014.6871137

Li, H., Hu, X.-B., Guo, X., Xu, Z., & van Gelder, P. H. A. J. M. (2016). A New Quantitative Method for Studying the Vulnerability of Civil Aviation Network System to Spatially Localized Hazards. International Journal of Disaster Risk Science, 7(3), 245–256. https://doi.org/10.1007/s13753-016-0098-1

Li, X., & Chen, X. (2018). Airport Simulation Technology in Airport Planning, Design and Operating Management. Applied and Computational Mathematics, 7(3), 130–138. https://doi.org/10.11648/j.acm.20180703.18

Liao, T.-Y., Hu, T.-Y., & Ko, Y.-N. (2018). A resilience optimization model for transportation networks under disasters. Natural Hazards, 93, 469–489. https://doi.org/10.1007/s11069-018-3310-3

Lin, Y., & Druzdzel, M. (1997). Computational Advantages of Relevance Reasoning in Bayesian Belief Networks. Proceedings of the Thirteenth Conference on Uncertainty in Artificial Intelligence (UAI1997), 335–342.

Liu, Y. J., Cao, W. D., & Ma, S. (2008, October). Estimation of arrival flight delay and delay propagation in a busy hub-airport. In 2008 Fourth International Conference on Natural Computation (Vol. 4, pp. 500-505). IEEE.

Lordan, O., Sallan, J. M., Simo, P., & Gonzalez-Prieto, D. (2014). Robustness of the air transport network. Transportation Research Part E: Logistics and Transportation Review, 68, 155–163. https://doi.org/10.1016/j.tre.2014.05.011

Lordan, O., Sallan, J. M., Simo, P., & Gonzalez-Prieto, D. (2015). Robustness of airline alliance route networks. Communications in Nonlinear Science and Numerical Simulation, 22(1–3), 587–595. https://doi.org/10.1016/j.cnsns.2014.07.019

Lordan, Sallan, J. M., Escorihuela, N., & Gonzalez-Prieto, D. (2016). Robustness of airline route networks. Physica A: Statistical Mechanics and Its Applications, 445, 18–26. https://doi.org/10.1016/j.physa.2015.10.053

Lucas P. (2001). Bayesian networks in medicine: a model-based approach to medical decision making. K-P. Adlassnig (ed.). Proceedings of the EUNITE workshop on Intelligent Systems in patient Care. Vienna, Austria, pp. 73-97.

Malandri, C., Briccoli, M., Mantecchini, L., & Paganelli, F. (2018). A Discrete Event Simulation Model for Inbound Baggage Handling. Transportation Research Procedia, 35, 295–304. https://doi.org/10.1016/j.trpro.2018.12.008

Malandri, C., Fonzone, A., & Cats, O. (2018). Recovery time and propagation effects of passenger transport disruptions. Physica A, 505, 7–17. https://doi.org/10.1016/j.physa.2018.03.028

Malandri, C., Mantecchini, L., & Reis, V. (2019). Aircraft turnaround and industrial actions: How ground handlers' strikes affect airport airside operational efficiency. Journal of Air Transport Management, 78, 23–32. https://doi.org/10.1016/j.jairtraman.2019.04.007

Malandri, Mantecchini, & Postorino. (2017). Airport Ground Access Reliability and Resilience of Transit Networks: A Case Study. Transportation Research Procedia, 27, 1129-1136. https://doi.org/10.1016/j.trpro.2017.12.022

Martinez, J. C., Trani, A. A., & Ioannou, P. G. (2001). Modeling airside airport operations using general-purpose, activity-based, discrete-event simulation tools. Transportation research record, 1744(1), 65-71.

Marzuoli, A., Boidot, E., Colomar, P., Guerpillon, M., Feron, E., Bayen, A., & Hansen, M. (2016). Improving Disruption Management with Multimodal Collaborative Decision-Making: A Case Study of the Asiana Crash and Lessons Learned. IEEE Transactions on Intelligent Transportation Systems, 17(10), 2699–2717. https://doi.org/10.1109/TITS.2016.2536733

Marzuoli, A., Boidot, E., Feron, E., Van Erp, P. B. C., Ucko, A., Bayen, A., & Hansen, M. (2016). Multimodal Impact Analysis of an Airside Catastrophic Event: A Case Study of the Asiana Crash. IEEE Transactions on Intelligent Transportation Systems, 17(2), 587–604. https://doi.org/10.1109/TITS.2015.2483743

Mattsson, L. G., & Jenelius, E. (2015). Vulnerability and resilience of transport systems - A discussion of recent research. Transportation Research Part A: Policy and Practice, 81, 16–34. https://doi.org/10.1016/j.tra.2015.06.002

Morales, O., Kurowicka, D., & Roelen, A. (2008). Eliciting conditional and unconditional rank correlations from conditional probabilities. Reliability Engineering and System Safety, 93(5), 699–710. https://doi.org/10.1016/j.ress.2007.03.020

Mota, M. (2015). Check-in allocation improvements through the use of a simulation–optimization approach. Transportation Research Part A: Policy and Practice. Retrieved from https://www.sciencedirect.com/science/article/pii/S0965856415001020

Mota, M. M., Boosten, G., De Bock, N., Jimenez, E., & de Sousa, J. P. (2017). Simulation-based turnaround evaluation for Lelystad Airport. Journal of Air Transport Management, 64, 21–32. https://doi.org/10.1016/j.jairtraman.2017.06.021

Mota, M. M., Scala, P., & Boosten, G. (2014, February). Simulation-based capacity analysis for a future airport. In 2014 Asia-Pacific Conference on Computer Aided System Engineering (APCASE) (pp. 97-101). IEEE.

Mota, M., & Flores, I. (2018). Revisiting the flaws and pitfalls using simulation in the analysis of aviation capacity problems. Case Studies on Transport Policy. https://doi.org/10.1016/j.cstp.2018.03.004

Mujalli, R. O., & De Oña, J. (2011). A method for simplifying the analysis of traffic accidents injury severity on two-lane highways using Bayesian networks. Journal of Safety Research, 42(5), 317–326. https://doi.org/10.1016/j.jsr.2011.06.010

Murray-Tuite, P. M. (2006). A comparison of transportation network resilience under simulated system optimum and user equilibrium conditions. In Proceedings - Winter Simulation Conference, pp. 1398–1405. https://doi.org/10.1109/WSC.2006.323240

Nakayama, H., Ansari, N., Jamalipour, A., & Kato, N. (2007). Fault-resilient sensing in wireless sensor networks. Computer Communications, 30(11–12), 2375–2384. https://doi.org/10.1016/J.COMCOM.2007.04.023

Neil Adger, W. (1999). Social vulnerability to climate change and extremes in coastal Vietnam. World Development, 27(2), 249–269. https://doi.org/10.1016/S0305-750X(98)00136-3

Neil, N. E. (2014). Decision Support Software for Probabilistic Risk Assessment Using Bayesian Networks. IEEE Software, 31(2), 21–26. https://doi.org/10.1109/MS.2014.32

Neil, M., Fenton, N., & Tailor, M. (2005). Using Bayesian networks to model expected and unexpected operational losses. Risk Analysis, 25(4), 963–972. https://doi.org/10.1111/j.1539-6924.2005.00641.x

NIAC (National Infrastructure Advisory Committee), (2009). Critical Infrastructure Resilience: Final report and recommendations. U.S. Department of Homeland Security, Washington D.C.

Norin, A., Granberg, T. A., Yuan, D., & Värbrand, P. (2012). Airport logistics – A case study of the turn-around process. Journal of Air Transport Management, 20, 31–34. https://doi.org/10.1016/j.jairtraman.2011.10.008

O'Regan, M. (2011). On the edge of chaos: European aviation and disrupted mobilities. Mobilities, 6(1), 21–30. https://doi.org/10.1080/17450101.2011.532649

Orwin, K. H., & Wardle, D. A. (2004). New indices for quantifying the resistance and resilience of soil biota to exogenous disturbances. Soil Biology and Biochemistry, 36(11), 1907–1912. https://doi.org/10.1016/J.SOILBIO.2004.04.036

Osei-Asamoah, A., & Lownes, N. E. (2014). Complex network method of evaluating resilience in surface transportation networks. Transportation Research Record. National Research Council. https://doi.org/10.3141/2467-13

Palumbo, R., Errico, A., Pascarella, D., Gargiulo, F., & Filippone, E. (2015). Modeling approach for resilience engineering of the future ATM system. In 15th AIAA Aviation Technology, Integration, and Operations Conference.

Palumbo, R., & Filippone, E. (2017). A quantitative approach to resilience engineering for the future ATM system: Case studies results. In 12th USA/Europe Air Traffic Management R and D Seminar.

Patriarca, R., Bergström, J., Di Gravio, G., & Costantino, F. (2018). Resilience engineering: Current status of the research and future challenges. Safety Science, 102, 79–100. https://doi.org/10.1016/J.SSCI.2017.10.005

Pearl, J. (1986). Fusion, propagation, and structuring in belief networks. Artificial Intelligence, 29(3), 241–288. https://doi.org/10.1016/0004-3702(86)90072-X

Pearl, J. (2011). Bayesian networks. UCLA: Department of Statistics, UCLA. Retrieved from https://escholarship.org/uc/item/53n4f34m

Pejovic, T., Noland, R. B., Williams, V., & Toumi, R. (2009). A tentative analysis of the impacts of an airport closure. Journal of Air Transport Management, 15(5), 241–248. https://doi.org/10.1016/j.jairtraman.2009.02.004

Pimm, S. (1991). The balance of nature? University of Chicago Press, Chicago, Illinois, USA.

Popper, K. R. (1959). The propensity interpretation of probability. The British journal for the philosophy of science, 10(37), 25-42.

Postorino, M. N., & Mantecchini, L. (2020). An Element-by-Element Approach for a Holistic Estimation of the Airport Carbon Footprint. In Sustainable Aviation (pp. 193–214). Springer International Publishing. https://doi.org/10.1007/978-3-030-28661-3_10

Postorino, M. N., Mantecchini, L., & Paganelli, F. (2019). Improving taxi-out operations at city airports to reduce CO2 emissions. Transport Policy, 80, 167–176. https://doi.org/10.1016/j.tranpol.2018.09.002

Pregenzer, A. L. (2011). Systems Resilience: A New Analytical Framework for Nuclear Nonproliferation. Albuquerque, NM: Sandia National Laboratories. Retrieved from http://www.ntis.gov/help/ordermethods.asp?loc=7-4-0#online

Reggiani, A., Nijkamp, P., & Lanzi, D. (2015). Transport resilience and vulnerability: The role of connectivity. Transportation Research Part A: Policy and Practice, 81, 4–15. https://doi.org/10.1016/j.tra.2014.12.012

Reichardt, U., Ulfarsson, G. F., & Pétursdóttir, G. (2018). Volcanic ash and aviation: Recommendations to improve preparedness for extreme events. Transportation Research Part A: Policy and Practice, 113, 101–113. https://doi.org/10.1016/j.tra.2018.03.024

Reichardt, U., Ulfarsson, G. F., & Pétursdóttir, G. (2019). Developing scenarios to explore impacts and weaknesses in aviation response exercises for volcanic ash eruptions in Europe. Journal of Air Transport Management, 79. https://doi.org/10.1016/j.jairtraman.2019.101684

Riskind, J. H., & Black, D. (2006). Cognitive Vulnerability. In Encyclopedia of Cognitive Behavior Therapy (pp. 122–126). Springer-Verlag. https://doi.org/10.1007/0-306-48581-8_37

Rodríguez-Núñez, E., & García-Palomares, J. C. (2014). Measuring the vulnerability of public transport networks. Journal of Transport Geography, 35, 50–63. https://doi.org/10.1016/j.jtrangeo.2014.01.008

Rodríguez-Sanz, Á., Gómez Comendador, F., Arnaldo Valdés, R., Cordero García, J., & Bagamanova, M. (2018). Uncertainty Management at the Airport Transit View. Aerospace, 5(2), 59. https://doi.org/10.3390/aerospace5020059

Rodríguez-Sanz, Á., Comendador, F. G., Valdés, R. A., & Pérez-Castán, J. A. (2018b). Characterization and prediction of the airport operational saturation. Journal of Air Transport Management, 69, 147–172. https://doi.org/10.1016/j.jairtraman.2018.03.002

Rodríguez-Sanz, Á., Comendador, F. G., Valdés, R. A., Pérez-Castán, J., Montes, R. B., & Serrano, S. C. (2019). Assessment of airport arrival congestion and delay: Prediction and reliability. Transportation Research Part C: Emerging Technologies, 98, 255–283. https://doi.org/10.1016/j.trc.2018.11.015

Rose, A. (2007). Economic resilience to natural and man-made disasters: Multidisciplinary origins and contextual dimensions. Environmental Hazards, 7(4), 383-398.

Rose, A., & Liao, S. Y. (2005). Modeling regional economic resilience to disasters: A computable general equilibrium analysis of water service disruptions. Journal of Regional Science, 45(1), 75–112. https://doi.org/10.1111/j.0022-4146.2005.00365.x

Roy, S., Xue, M., & Sridhar, B. (2017). Vulnerability metrics for the airspace system. In Proceedings of the 2017 FAA/Eurocontrol Air Traffic Management Research and Development Seminar.

Schinwald, C., Plötner, K. O., & Hornung, M. (2016). Using airport fast-time simulation models to increase the quality of airport capacity utilization studies. In AIAA Modeling and Simulation

Technologies Conference. American Institute of Aeronautics and Astronautics Inc, AIAA. https://doi.org/10.2514/6.2016-0421

Royal Schiphol Group, (2018). 2018 Annual Report. Schiphol, The Netherlands. Retrieved from https://www.annualreportschiphol.com/about-us/facts-and-figures

Schmidt, M. (2017). A review of aircraft turnaround operations and simulations. Progress in Aerospace Sciences, 92, 25–38. https://doi.org/10.1016/j.paerosci.2017.05.002

Schmidt, M., Engelmann, M., Brügge-Zobel, T., Hornung, M., & Glas, M. (2016). PAXelerate - An Open Source Passenger Flow Simulation Framework for Advanced Aircraft Cabin Layouts. In 54th AIAA Aerospace Sciences Meeting. Reston, Virginia: American Institute of Aeronautics and Astronautics. https://doi.org/10.2514/6.2016-1284

Schmidt, M., Heinemann, P., & Hornung, M. (2017). Boarding and Turnaround Process Assessment of Single- and Twin-Aisle Aircraft. In 55th AIAA Aerospace Sciences Meeting. Reston, Virginia: American Institute of Aeronautics and Astronautics. https://doi.org/10.2514/6.2017-1856

Seeliger, L., & Turok, I. (2013). Towards sustainable cities: Extending resilience with insights from vulnerability and transition theory. Sustainability (Switzerland), 5(5), 2108–2128. https://doi.org/10.3390/su5052108

Senguttuvan, P. S. (2006). Economics of the airport capacity system in the growing demand of air traffic–a global view (No. 1427-2016-118528).

Shavell, Z. A. (2001). Effects of schedule disruptions on the economics of airline operations. Progress in Astronautics and Aeronautics, 193, 115-126.

Soria, M., Lordan, O., & Sallan, J. M. (2017). Heuristics of node selection criteria to assess robustness of world airport network. Chinese Journal of Aeronautics, 30(4), 1473–1480. https://doi.org/10.1016/j.cja.2017.04.012

Spirtes, P., & Meek, C. (1995, August). Learning Bayesian networks with discrete variables from data. In KDD (Vol. 1, pp. 294-299).

Stevenson, A. (2011). Oxford dictionary of English. Oxford University Press, Oxford, UK. Retrieved from https://books.google.it/books?hl=it&lr=&id=anecAQAAQBAJ&oi=fnd&pg=PR5&dq=oxford+dictionary+of+english&ots=T_ju9shHzT&sig=RX-cXAUpzuIxjpqCuKpc_2Gudlk&redir_esc=y#v=onepage&q=oxford dictionary of english&f=false

Stroeve, S. H., Bosse, T., Blom, H. A., Sharpanskykh, A., & Everdij, M. H. (2013). Agent-based modelling for analysis of resilience in ATM. Proceedings of the Third SESAR Innovation days. Stockholm (Sweden), November.

Stroeve, S. H., & Everdij, M. H. C. (2017). Agent-based modelling and mental simulation for resilience engineering in air transport. Safety Science, 93, 29–49. https://doi.org/10.1016/j.ssci.2016.11.003

Stroeve, S. H., Everdij, M. H. C., & Blom, H. A. P. (2011). Studying hazards for resilience modelling in ATM: Mathematical Approach towards Resilience Engineering in ATM (MAREA). In SIDs 2011 - Proceedings of the SESAR Innovation Days.

Sun, X., Gollnick, V., & Wandelt, S. (2017). Robustness analysis metrics for worldwide airport network: A comprehensive study. Chinese Journal of Aeronautics, 30(2), 500–512. https://doi.org/10.1016/j.cja.2017.01.010

Sun, X., & Wandelt, S. (2017). Does the Chinese airline network become more robust over time? In 2017 2nd International Conference on Reliability Systems Engineering, ICRSE 2017. https://doi.org/10.1109/ICRSE.2017.8030725

Sutrisnowati, R. A., Bae, H., & Song, M. (2015). Bayesian network construction from event log for lateness analysis in port logistics. Computers & Industrial Engineering, 89, 53-66.

Testa, A. C., Furtado, M. N., & Alipour, A. (2015). Resilience of coastal transportation networks faced with extreme climatic events. Transportation Research Record, 2532, 29–36. https://doi.org/10.3141/2532-04

Thompson, K. H., & Tran, H. T. (2018). Application of a Defender-Attacker-Defender Model to the U.S. Air Transportation Network. In 2018 IEEE International Symposium on Technologies for Homeland Security, HST 2018. https://doi.org/10.1109/THS.2018.8574199

Thompson, K. H., & Tran, H. T. (2019). Operational Perspectives Into the Resilience of the U.S. Air Transportation Network Against Intelligent Attacks. IEEE Transactions on Intelligent Transportation Systems. https://doi.org/10.1109/TITS.2019.2909177

Trucco, P., Minato, N., & Careri, N. (2014). Resilience of transport systems under disaster: Simulation-based analysis of 2011 tsunami in Japan. In IEEE International Conference on Industrial Engineering and Engineering Management (pp. 487–491). https://doi.org/10.1109/IEEM.2013.6962459

Vidosavljević, A. and Tošić, V. (2010). Modelling of turnaround process using Petri nets, Proceedings of the 14th ATRS World Conference, 2010, Porto, Portugal, pp 1–13.

Vlek, C. S., Prakken, H., Renooij, S., & Verheij, B. (2014). Building Bayesian networks for legal evidence with narratives: a case study evaluation. Artificial Intelligence and Law, 22(4), 375–421. https://doi.org/10.1007/s10506-014-9161-7

Voltes-Dorta, A., Rodríguez-Déniz, H., & Suau-Sanchez, P. (2017a). Passenger recovery after an airport closure at tourist destinations: A case study of Palma de Mallorca airport. Tourism Management, 59, 449–466. https://doi.org/10.1016/j.tourman.2016.09.001

Voltes-Dorta, A., Rodríguez-Déniz, H., & Suau-Sanchez, P. (2017b). Vulnerability of the European air transport network to major airport closures from the perspective of passenger delays: Ranking the most critical airports. Transportation Research Part A: Policy and Practice, 96, 119–145. https://doi.org/10.1016/j.tra.2016.12.009

Von Ferber, C., Holovatch, T., Holovatch, Y., & Palchykov, V. (2009). Public transport networks: Empirical analysis and modeling. European Physical Journal B, 68(2), 261–275. https://doi.org/10.1140/epjb/e2009-00090-x

Voulgarellis, P. G., Christodoulou, M. A., & Boutalis, Y. S. (2005). A MATLAB based simulation language for aircraft ground handling operations at hub airports (SLAGOM). In Proceedings of the 20th IEEE International Symposium on Intelligent Control, ISIC '05 and the 13th Mediterranean Conference on Control and Automation, MED '05 (Vol. 2005, pp. 334–339). https://doi.org/10.1109/.2005.1467037

Vugrin, E. D., Warren, D. E., Ehlen, M. A., & Camphouse, R. C. (2010). A framework for assessing the resilience of infrastructure and economic systems. In Sustainable and resilient critical infrastructure systems (pp. 77-116). Springer, Berlin, Heidelberg.

Walker, B., Holling, C. S., Carpenter, S. R., & Kinzig, A. P. (2004). Resilience, Adaptability and Transformability in Social-ecological Systems. Ecology and Society, 9(2), art5. https://doi.org/10.5751/ES-00650-090205

Wan, C., Yang, Z., Zhang, D., Yan, X., & Fan, S. (2018). Resilience in transportation systems: a systematic review and future directions. Transport reviews, 38(4), 479-498. https://doi.org/10.1080/01441647.2017.1383532

Weick, K. E., & Sutcliffe, K. M. (2013). Managing the unexpected: resilient performance in an age of uncertainty. Jossey-Bass. Retrieved from https://books.google.it/books?hl=it&lr=&id=GU55MJOp1OcC&oi=fnd&pg=PR9&dq=weick+resilience+&ots=0Fy2d7zOIr&sig=gphmub7utsLRslzDOtVrfcwoRz0#v=onepage&q=weick resilience&f=false

Westrum, R. (2018). A Typology of Resilience Situations. In Resilience Engineering (pp. 55–65). CRC Press, USA. https://doi.org/10.1201/9781315605685-8

Wilkinson, S. M., Dunn, S., & Ma, S. (2012). The vulnerability of the European air traffic network to spatial hazards. Natural Hazards, 60(3), 1027–1036. https://doi.org/10.1007/s11069-011-9885-6

Woods, D. D. (2015). Four concepts for resilience and the implications for the future of resilience engineering. Reliability Engineering & System Safety, 141, 5–9. https://doi.org/10.1016/j.ress.2015.03.018

Woods, D. D. (2017). Essential Characteristics of Resilience. In Resilience Engineering (pp. 21–34). CRC Press. https://doi.org/10.1201/9781315605685-4

Woods, D. D., & Wreathall, J. (2008). Stress-strain plots as a basis for assessing system resilience. Resilience engineering perspectives, 1, 145-161.

Worton, K. E. (2012). Using socio-technical and resilience frameworks to anticipate threat. In Proceedings - 2nd Workshop on Socio-Technical Aspects in Security and Trust, STAST 2012, Co-located with 25th IEEE Computer Security Foundations Symposium, CSF 2012 (pp. 19–26). https://doi.org/10.1109/STAST.2012.16

Wu, C., & Caves, R. E. (2004). Modelling and optimization of aircraft turnaround time at an airport. Transportation Planning and Technology, 27(1), 47–66. https://doi.org/10.1080/0308106042000184454

Wuellner, D. R., Roy, S., & D'Souza, R. M. (2010). Resilience and rewiring of the passenger airline networks in the United States. Physical Review E - Statistical, Nonlinear, and Soft Matter Physics, 82(5). https://doi.org/10.1103/PhysRevE.82.056101

Yan, B., Zhou, Q., & Luo, R. (2013). Vulnerability analysis of complex transportation network. Advances in Transportation Studies, (SPECIAL IS), 3–8.

Yan, S., Shieh, C. Y., & Chen, M. (2002). A simulation framework for evaluating airport gate assignments. Transportation Research Part A: Policy and Practice, 36(10), 885–898. https://doi.org/10.1016/S0965-8564(01)00045-3

Yoo, S., & Yeo, H. (2016). Evaluation of the resilience of air transportation network with adaptive capacity. International Journal of Urban Sciences, 20, 38–49. https://doi.org/10.1080/12265934.2016.1166979

Youn, B. D., Hu, C., & Wang, P. (2011). Resilience-Driven System Design of Complex Engineered Systems. Journal of Mechanical Design, 133(10). https://doi.org/10.1115/1.4004981

Yuan, C., & Druzdzel, M. (2003). An importance sampling algorithm based on evidence pre-propagation. In Proceedings of the 19th Annual Conference on Uncertainty in Artificial Intelligence (UAI03). Retrieved from http://arxiv.org/abs/1212.2507

Zhang, X., Miller-Hooks, E., & Denny, K. (2015). Assessing the role of network topology in transportation network resilience. Journal of Transport Geography, 46, 35–45. https://doi.org/10.1016/j.jtrangeo.2015.05.006

Zhou, Y., Wang, J., & Yang, H. (2019). Resilience of Transportation Systems: Concepts and Comprehensive Review. IEEE Transactions on Intelligent Transportation Systems, 1–15. https://doi.org/10.1109/tits.2018.2883766

Zhu, Y., Ozbay, K., Xie, K., & Yang, H. (2016). Using big data to study resilience of taxi and subway trips for Hurricanes Sandy and Irene. Transportation Research Record, 2599, 70–80. https://doi.org/10.3141/2599-09

Zuniga, C., Delahaye, D., & Piera, M. A. (2011). Integrating and sequencing flows in Terminal Maneuvering Area by evolutionary algorithms. In 2011 IEEE/AIAA 30th Digital Avionics Systems Conference (p. 2A1-1-2A1-11). IEEE. https://doi.org/10.1109/DASC.2011.6095980