

REGULAR PAPER

Analysis and modelling of airport resilience, robustness, and vulnerability: impact of COVID-19 pandemic disease

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Received: 10 November 2020; **Revised:** 6 January 2022; **Accepted:** 21 February 2022

Keywords: Airports; Resilience; Robustness; Vulnerability; Disruptive events; Performances; Indicators; Methodology

Abstract

Airports have been frequently affected by different internal and external disruptive events, which generally deteriorated their planned/regular performances. Their resilience is defined as the ability to withstand and maintain a certain level of functionality of performances compared to their reference regular/planned level during the impact of disruptive events and to recover reasonably rapidly afterwards. Robustness is defined as the level of saved functionality of performances compared to their planned/regular level, enabling continuous operations during the impact of disruptive events. The level of deteriorated functionality compared to that of the planned/regular functionality of performances represents their vulnerability. This paper develops a methodology for assessing resilience, robustness and vulnerability of airports affected by a given disruptive event(s). The methodology consists of analytical models of indicators of operational, economic, social and environmental performances of airports and other main actors/stakeholders involved. These indicators are used as figures-of-merit in analytical models for assessing their cumulative and time-dependent resilience, robustness, and vulnerability. The methodology is applied to assess resilience, robustness and vulnerability of two large airports – LHR (London Heathrow, UK) and NYC JFK (John F. Kennedy, US) – affected by a global and lasting external disruptive event – the COVID-19 pandemic disease. Based on the indicators of operational and economic performances, the results indicate very low resilience and robustness and very high vulnerability of both airports and their other main actors/stakeholders involved. Their resilience and robustness based on the indicators of social and environmental performances were not substantively different from the corresponding vulnerability. In absolute terms, LHR airport has been affected stronger than its NYC JFK counterpart. Savings in costs/externalities during the observed period under the given conditions have modestly compensated for total losses of both airports and their main actors/stakeholders involved.

Nomenclature

<i>ACR</i>	is the average annual incident/accident rate at the given airport (number/ATM)
<i>ATC</i>	Air Traffic Control
<i>ATM</i>	Air Transport Movement
<i>CO_{2e}</i>	Carbon Dioxide Equivalents
<i>curru</i>	currency unit
<i>GBP</i>	British Pound Sterling
<i>GDP</i>	Gross Domestic Product
<i>n₁₁(t)</i>	the number of cancelled ATMs at the given airport at time (<i>t</i>) ATMs
<i>pr_{21/ap}</i>	the average loss of profits (difference between the revenues and costs) of the given airport from cancelled ATM at time (<i>t</i>) (curru/ATM)
<i>pr_{22/ca}</i>	the average loss of profits (difference between revenues and costs) by airlines from cancelled ATMs at the given airport at time (<i>t</i>) (curru/ATM)
<i>pr_{23/ATC}</i>	the average loss of profits (difference between revenues and costs) by ATC from cancelled ATMs at the given airport at time (<i>t</i>) (curru/ATM)

gdP_{23}	the average loss of contribution to GDP from cancelled ATMs at the given airport at time (t) (curru/ATM)
$C_{32/n}$	the average cost of noise protection (curru/dBA-ATM)
$C_{33/ac}$	the cost of an ATM incident/accident (includes the cost of injuries, fatalities both on board the aircraft and on the ground, and loss of aircraft) (curru/event)
$C_{41/GHG}$	the average price/cost of GHG emissions (curru/ton CO _{2e})
$\frac{L_{E/a}, L_{E/d}}{GDP_{0/23}(t) \equiv F_{0/23}(t)}$	is the average noise per arrival and departure, respectively (dBA/ATM)
$GDP_{0/23}(t) \equiv F_{0/23}(t)$	the contribution to GDP by the planned/scheduled ATMs at time (t) (curru/ATM)
$N_{0/11}(t) \equiv F_{0/11}(t)$	the number of reference planned/scheduled ATMs at time (t)
$PR_{21}(t) \equiv F_{0/21}(t)$	the profits (difference between revenues and costs) of the airport from the reference planned/scheduled ATMs at time (t) (curru/ATM)
$PR_{22}(t) \equiv F_{0/22}(t)$	the profits of the aviation industry (airport, airlines and ATC) from the reference planned/scheduled ATMs at time (t) (curru/ATM)
$FOM_{0/ij}$	the reference (planned/regular) value of the loss indicator (i) of performance (j)
$FOM_{0/kl}$	the regular/planned value of the savings indicator (k) of performance (l)
N	the number of loss performances of the given airport affected by the given disruptive event
N_j	the number of loss indicators of performance (j)
M	the number of savings performances affected by disruptive events
M_k	the number of savings indicators of performance (k)
i	the loss indicator of performance (j) of the given airport
j	the performance of the given airport
t	the time during the observed period
k	the savings performance of the given airport
l	the indicator of savings performance (k) of the given airport
\bar{q}_n	the average quantity of GHG emissions (ton/ATM)
α_{ij}	the rate of deterioration of the loss indicator (i) of performance (j)
β_{ij}	the rate of recovery of the loss indicator (i) of performance (j)
γ_{kl}	the rate of deterioration of the savings indicator (k) of performance (l)
δ_{kl}	the rate of recovery of the savings indicator (k) of performance (l)
USD	US Dollar
\bar{w}_n	the average delay (min/ATM)

1.0 Introduction

Resilience, robustness, and vulnerability of engineering systems and civil infrastructures can be considered in terms of four dimensions of performances: (1) technical/technological, (2) organisational, (3) social, and (4) economic [1–3]. In such context, resilience is defined as: (i) the sum of the passive survival rate (reliability) and the proactive survival rate (restoration), thus reflecting their robustness while operating under disruptive conditions [4, 5]; (ii) the intrinsic ability to adjust the system's functionality in the presence of disturbances and unpredicted changes [6]; and (iii) the ability to sustain external and internal disruptions without discontinuity of functioning or, if these functions are disconnected, to resume them fully and rapidly [7]. Robustness is considered as the ability of these systems to maintain their affected performances as close as possible to the planned/regular level during the impact of a given disruptive event. Vulnerability is expressed by the difference between the planned/regular and retained/saved level of performances during the impact of a given disruptive event.

In particular, airports as components of the air transport system, which is also a sub-component of the engineering systems, have been affected by different disruptive events. In such case, their resilience can be considered as the ability to withstand and maintain a certain level of functionality, i.e. to operate at the certain although deteriorated level of performances during the impact of disruptive events and to recover in a reasonable time afterwards [8, 9]. Robustness can be considered as the level of saved and maintained functionality of performances compared to the planned/regular one during the impact of the disruptive event. Vulnerability expresses the extent of deterioration of the planned/regular performances [10, 11].

As airports also belong to civil infrastructures, resilience, robustness, and vulnerability can be considered in terms of functionality of their infrastructural, technical/technological, operational, economic, social, and environmental performances. These performances can be affected by different external and internal disruptive events and may consequently deteriorate to certain including zero level. Both regular/planned and affected performances can be expressed by the corresponding indicators during the impact of a given disruptive event and afterwards, during their recovery. Airports affected by different disruptive events undertake different contingency measures. These usually embrace reduction of the airside and landside planned/regular capacity thus causing long delays and/or cancellation of airline flights. Some measures also prevent access of air passenger and cargo demand to the airport and airlines' planned/regular unaffected capacity, causing their underutilisation and cancellation of flights, respectively. Consequently, disruptive events and related contingency measures affect the functionality of planned/nominal performances of airports and other main actors/stakeholders involved. Apart from airports, these other main actors/stakeholders are: air passengers and cargo shippers, airlines, ATC (Air Traffic Control), local communities, and the society at the regional, national and international level. Due to the nature of air transport operations, local impact of some disruptive events at one airport can spread wider to the connected airports, which would otherwise stay unaffected. Moreover, some disruptive events happening on a rather wide and even global scale can impact several airports simultaneously.

This paper deals with an analysis and modelling of resilience, robustness and vulnerability of airports affected by a given disruptive event(s). In addition to this introductory section, the paper consists of four other sections. Section 2 describes some disruptive events affecting the functionality of performances of airports and other related main actors/stakeholders involved. Section 3 deals with developing a methodology consisting of analytical models of indicators of airport performances relevant for particular actors/stakeholders involved and analytical models for assessing resilience, robustness, and vulnerability using these indicators as figures-of-merit. Section 4 presents an application of these models to LHR (London Heathrow, UK) and JFK (John F. Kennedy, US) affected by a large-scale external disruptive event – the COVID-19 pandemic disease. The last section summarises some conclusions.

2.0 Some disruptive events and their impacts

2.1 General

A disruptive event is defined as any event affecting the planned/regular functionality of performances of transport systems, safety and security of persons, goods and properties either internally, at surrounding communities, or the environment. Serious disruptive events considered as disastrous are generally classified as natural, technological and complex [12]. In general, the first class embraces events such as droughts, storms (hurricanes, tornadoes, blizzards, tsunamis, cyclones), earthquakes, volcanic eruptions, epidemic/pandemic diseases, floods, landslides and extreme temperatures. The second class embraces human-made transport and miscellaneous accidents, such as terrorist attacks, revolutions, unrests, etc. The last class embraces combinations of types of the previous two classes [13–15].

In the given context, disruptive events affecting regular/planned functionality of performance(s) of engineering, transport systems, airports and the entire air transport system (airports, airlines, ATC (Air Traffic Control)) are generally classified as internal and external. Internal disruptive events occurring within and external disruptive events occurring outside airports, airlines and ATC affect the functionality of their planned/regular performances [11, 16–18].

2.2 Internal disruptive events

Some internal disruptive events affecting regular/planned functionality of airport performances are airport-related air traffic incidents/accidents, industrial actions of the aviation staff, failures of the airport-based facilities and equipment, and collapse of the dominant airline.

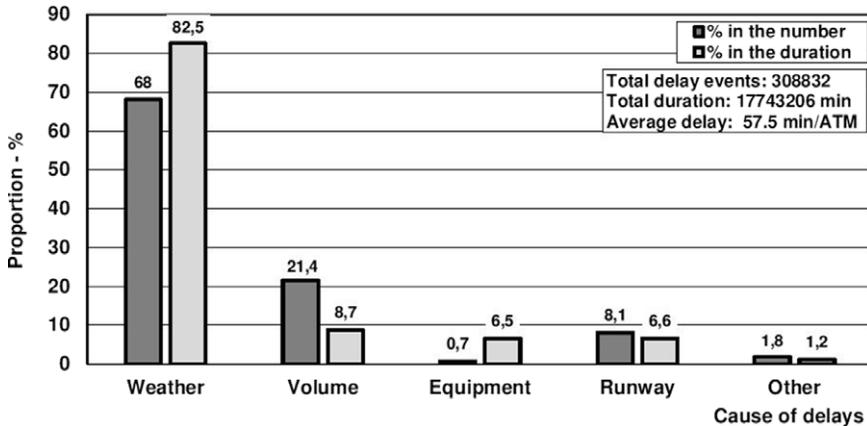


Figure 1. Main causes and their proportion in the number and duration of airline flight delays at 45 US main airports (Period: Year: 2019) [37].

- *Airport-related air traffic incidents/accidents* caused by the system's either internal or external causes have most frequently happened during taking-offs, landings, and at some cases these were collisions during the taxiing phase of flights. They usually required airports to be temporarily closed and consequently caused long delays and cancellations of airline flights scheduled during the time they were being dealt with [19–21].
- *Industrial actions of the aviation staff* in one or all three main components – airports, airlines, and ATC – usually stop the operations, compromise utilisation of the corresponding regular/planned capacities, and consequently result in rather long delays and cancellations of affected flights [22, 23].
- *Failures of airport-based facilities and equipment* embrace events that happen at the radio-navigation facilities in the airside area (ILS (Instrument Landing System), runway, taxiway and apron/gate lights) and in the landside area (computer systems, lights and the overall power system, i.e. those for handling passengers and their baggage). Happening randomly in most cases they all caused rather long delays and cancellations of the affected airline flights [24–26].
- *Collapses of dominant airline(s)* usually resulted in cancelling all flights at the affected airports. These airports temporarily lost their previous passenger and air cargo demand, which substantively compromised their revenues, costs and profits [27–29].

2.3 External disruptive events

Some common external disruptive events affecting the functionality of regular/planned performances of airports and the entire air transport system are severe weather, natural disasters, epidemic/pandemic diseases and terrorist threats/attacks.

- *Severe weather* embraces meteorological phenomena such as typhoons, heavy rain, heavy snow and thunderstorms [30–33].

Generally, the above-mentioned weather phenomena were relatively precisely predictable and thus enabled preparation and implementation of contingency measures – most frequently in terms of imposing delays and in some cases cancelling of the affected airline flights [34–36]. For example, Fig. 1 shows that severe weather is one of the main causes of airline flight delays at the US main airports during the observed period.

- *Natural disasters* embrace phenomena such as earthquakes, tsunamis and volcanic eruptions. In general, the time of occurrence and the extent/scope of impact of earthquakes are difficult to

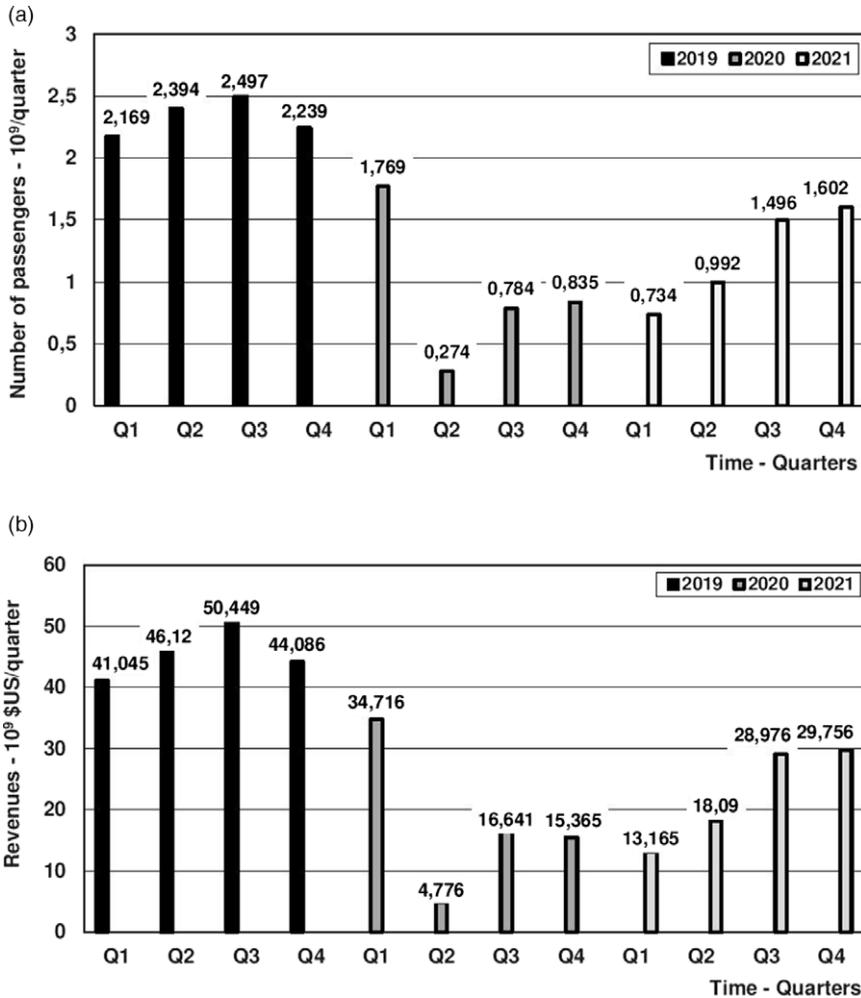


Figure 2. Actual and predicted global impact of COVID-19 pandemic disease on the world’s airports [41]. (a) Passengers (Period: 2019, 2020, 2021); (b) Revenues (Period: 2019, 2020, 2021).

predict. In addition to repairing the physical damage and restoring the planned/regular functionality of performances of the affected airports, secondary impacts materialised as general panic and harmful rumours, shortages of supplies and looting, etc. were also contained in the scope of contingency measures [3, 38]. Volcanic eruptions usually constrained the use of the affected airspace, causing delays of airline flights and consequently their planned/regular handling at airports [39, 40].

- *Epidemic/pandemic diseases* do not directly affect airports and air transport system’s regular/planned functionality of performances. In general, they require implementation of contingency/restrictive measures preventing access of users – air passengers to the airport and airline flights and available capacities at their planned/regular operating level. Consequently, capacities of airports remain underutilised and airline flights are cancelled. Figure 2(a, b) shows the example of the world’s airports affected by the most recent and still ongoing COVID-19 pandemic disease in the years 2019, 2020 and 2021 [41–44].

Figure 2(a) shows that compared to the last quarter (Q4) in 2019, the number of passengers at the world’s airports decreased in the first quarter (Q1) of the year 2020 by about 23%. The spreading impact of

COVID-19 and tightening of the contingency/restrictive measures caused further decrease in passenger numbers by about 89% in quarter 2 (Q2) of the year 2020. During the remainder of the considered period, this decrease is expected to remain at about 70% in the middle to about 33% in the last quarter (Q4) of the year 2021. During the observed period, Q1-2020-Q4-2021, the total expected loss of the number of passengers is expected to be about 70%. Figure 2(b) shows a similar impact on the airports. Compared to the year 2019, the total revenues decreased by about 65% in the year 2020 and are expected to decrease by about 55% in the year 2021. In addition to the above-mentioned direct impacts, the predicted economic trends are expected to mainly drive the global air passenger demand after the end of this pandemic.

- *Terrorist threats/attacks* affected airports and consequently airlines, as well. In most cases, these events required closure of the airports and surrounding airspace, which consequently caused relatively long delays, cancellation, and termination of the affected airline flights [45–47].

2.4 Summary of the impacts of disruptive events

The above-mentioned disruptive events and applied contingency measures can generally affect functionality of airport performances on a local (a single airport), regional (a few close airports) and global (the airports of a country, continent, and/or even several continents) scale. Independently of the scale, the measure of reducing the airport airside and landside capacity¹ causes longer delays and in some extreme cases – cancellation of the affected airline flights.

In particular, airports, airlines and ATC generally lose profits and the society contribution to GDP (Gross Domestic Product) from the cancelled flights [48]. When particular disruptive events are expected to last for a rather long time (weeks, months, years as for example in the case of COVID-19 pandemic disease), contingency measures preventing substantive and/or complete access of air passenger demand to the unaffected available airport and airline capacities mainly require their balancing. For example, multi-runway airports close some of the runways in addition to closing their air passenger terminals. Airlines cancel prospectively low occupied and/or empty flights, ground and conserve parts of their fleets. ATC usually reconfigures the airspace under its jurisdiction. They all also reduce operating staff and even make a part of it redundant. Also in this case, airports, airlines and ATC generally lose profits and the society contribution to GDP (Gross Domestic Product). However, some costs of impacts of cancelled airline flights and related airport and ATC services on the society and environment as internationalised externalities can be saved.

3.0 Methodology for assessing resilience, robustness, and vulnerability of airports

3.1 Literature review

Research on resilience, robustness and vulnerability of transport and the air transport system has been growing over the past decades. An overview of the existing research embracing 144 academic references mostly from scientific journals indicates that 11 research efforts deal explicitly with the resilience of transport systems [49]. This has been followed by more recent reviews. In both cases, the related research generally deals with the concept, definition and qualitative and quantitative assessments of resilience [49–51]. The research on air transport system resilience is generally focused on analysing and modelling topology, dynamics (indirect connectivity and passenger dynamics, air traffic jams and epidemic spreading, related costs), and vulnerability of airline networks affected by particular extreme disruptive events [11, 49, 52–56]. The costs of impacts of disruptive events affecting the airline hub airport(s) have also been the subject of intensive research [18, 57–61]. Moreover, some rather academic research deals with defining and understanding disturbance, resilience and robustness of the ATC system, including the development of their qualitative and quantitative measures [62, 63].

¹For example, at US airports, switching from the higher runway capacity VFR (Visual Flight Rules) to the lower runway capacity (Instrument Flight Rules) operations due to severe weather usually causes unplanned delays of affected airline flights (48).

3.2 Objectives and assumptions

Resilience, robustness and vulnerability of airports can be expressed by the functionality of their operational, economic, social and environmental performances during and after the impact of disruptive events. This functionality can be quantified by the corresponding indicators of performances estimated under given conditions. At directly affected airport(s), deterioration of the functionality of performances generally happens due to a gradual or immediate reduction in the number of handled flights compared to the number of handled flights under planned/regular conditions. This can be due to a reduction in the airport capacity, demand, or both simultaneously. Under such conditions, the indicator of operational performances can be the actual number of handled flights. Indicators of economic performances can be the airport and the aviation industry's (airport, airline and ATC (Air Traffic Control)) profits and contribution to the overall social welfare – GDP (Gross Domestic Product). Indicators of social performances can be the costs of airline and air passenger delays, airport noise and air traffic incidents/accidents. Indicators of environmental performances can be the costs of GHG (Green House Gases) emissions. These costs are internalised as externalities. The values of all the above-mentioned indicators directly depend on the number of handled flights.

At indirectly affected airports, the functionality of performances expressed by the above-mentioned indicators is compromised by the affected flights to/from the directly affected airport(s). In both cases, these indicators can be used as figures-of-merit for assessing the resilience, robustness and vulnerability of the affected airports under given conditions.

The main objectives of this research are to develop a methodology for assessing resilience, robustness and vulnerability of airports affected by a given disruptive event. The methodology consists of analytical models of indicators of performances and analytical models of resilience, robustness and vulnerability of a given airport and it uses these indicators as figures-of-merit. These models are based on the following assumptions:

- The average values of indicators of operational, economic, social and environmental performances of the given airports and other actors/stakeholders involved from the period before the impact of a given disruptive event are used as reference values of their corresponding functionality
- A given disruptive event actually affects the given airports and other actors/stakeholders involved indirectly, by requiring implementation of contingency/restrictive measures that prevent access of users-air passenger demand, to unaffected airport and airline flights capacities at the reference (planned/regular) level prior to being affected
- The impact of the given disruptive event on the air cargo demand and related functionality of performances of airport, airlines, ATC services is not considered
- The resilience, robustness, and vulnerability of the given airport based on the functionality of particular performances are assessed only during the impact of the given disruptive event; this implies that the phase until their complete recovery is not considered, due to the specificity of the continued impact of the considered disruptive event

3.3 Models of the indicators of performances

Analytical models of indicators of the above-mentioned performances for an airport directly affected by a given disruptive event are given in Table 1.

In Table 1, indicators of economic, social and environmental performances are expressed in monetary terms and are directly dependent of the indicator of operational performances – the number of ATMs (Air Transport Movement(s)). Economic performances of the aviation industry (airport, airlines and ATC) are expressed by the losses of its profits, and those of the society as losses of the contribution to GDP (social welfare) from the cancelled ATMs. Furthermore, social and environmental performances are improved due a reduction/savings in the costs of impacts on the society and environment from these

Table 1. Models of indicators of performances during the impact of a given disruptive event as figures-of-merit for assessing resilience, robustness, and vulnerability

Indicator	Main Actors/Stakeholders
1) Operational performances	Airport
• Cancelled ATMs – losses of planned/regular traffic (-)	$n_{11}(t) \tag{1}$ <p>where $n_{11}(t)$ – is the number of cancelled ATMs at the given airport at time (t) (ATMs).</p>
2) Economic performances	Airport
• Profits-losses from cancelled ATMs (-)	$PR_{21/ap}(t) = n_{11}(t) \cdot pr_{21/ap} \tag{2a}$ <p>where $pr_{21/ap}$ – is the average loss of profits (difference between the revenues and costs) of the given airport from cancelled ATM at time (t) (curru/ATM).</p>
	Aviation industry (airport, airlines, ATC)
• Profits – losses from cancelled ATMs (-)	$PR_{22/ati} = n_{11}(t) \cdot (PR_{21/ap} + pr_{22/al} + pr_{23/ATC}) \tag{2b}$ <p>where $pr_{22/ca}$ – is the average loss of profits (difference between revenues and costs) by airlines from cancelled ATMs at the given airport at time (t) (curru/ATM); and $pr_{23/ATC}$ – is the average loss of profits (difference between revenues and costs) by ATC from cancelled ATMs at the given airport at time (t) (curru/ATM).</p>
	Society
• Contribution to GDP – losses from cancelled ATMs (-)	$GDP_{23}(t) = n_{11}(t) \cdot gdp_{23} \tag{2c}$ <p>where gdp_{23} – is the average loss of contribution to GDP from cancelled ATMs at the given airport at time (t) (curru/ATM).</p>
3) Social and environmental performances	Aviation industry (airport, airlines, ATC), air passengers, local community
• Cost of delays – savings from cancelled ATMs (+)	$CD_{31}(t) = n_{11}(t) \cdot \bar{w}_{31} \cdot c_{31/d} \tag{3a}$ <p>where \bar{w}_n – is the average delay (min/ATM); $c_{31/d}$ – is the average cost per unit of delay (curru/min).</p>
• Cost of noise – savings from cancelled ATMs (+)	$CN_{32}(t) = n_{11}(t) \cdot (\overline{L_{E/a}} + \overline{L_{E/d}}) \cdot c_{32/n} \tag{3b}$ <p>where $\overline{L_{E/a}}, \overline{L_{E/d}}$ – is the average noise per arrival and departure, respectively (dBA/ATM); $c_{32/n}$ – is the average cost of noise protection (curru/dBA-ATM).</p>

Table 1. *Continued.*

Indicator	Main Actors/Stakeholders
3) Social and environmental performances	Aviation industry (airport, airlines, ATC), air passengers, local community
<ul style="list-style-type: none"> • Cost of air traffic inc./acc. – savings from cancelled ATMs (+) 	$CAC_{33}(t) = n_{11}(t) \cdot ACR \cdot c_{33/ac} \quad (3c)$ <p>where <i>ACR</i> – is the average annual incident/accident rate at the given airport (number/ATM); <i>c_{33/ac}</i> – is the cost of an ATM incident/accident (includes the cost of injuries, fatalities both on board the aircraft and on the ground, and loss of aircraft) (curru/event).</p>
<ul style="list-style-type: none"> • Cost/externalities of GHG emissions – savings from cancelled ATMs (+) 	$CEM_{34}(t) = n_{11}(t) \cdot \bar{q}_n \cdot p_{34/GHG} \quad (4)$ <p>where \bar{q}_n – is the average quantity of GHG emissions (ton/ATM); <i>c_{41/GHG}</i> – is the average price/cost of GHG emissions (curru/tonCO_{2e}) (CO_{2e} – Carbon Dioxide Equivalents).</p>

ATM – One arrival or one departure; (+) – Positive influence of cancelled ATMs; (–) – Negative influence of cancelled ATMs; curru – currency unit (GBP – British Pound Sterling; USD – US Dollar).

Table 2. *Reference indicators of performances under planned/regular conditions as figures-of-merit for assessing resilience, robustness, and vulnerability*

$N_{0/11}(t) \equiv F_{0/11}(t)$	is the number of reference planned/scheduled ATMs at time (<i>t</i>).
$PR_{21}(t) \equiv F_{0/21}(t)$	are the profits (difference between revenues and costs) of the airport from the reference planned/scheduled ATMs at time (<i>t</i>) (curru/ATM).
$PR_{22}(t) \equiv F_{0/22}(t)$	are the profits of the aviation industry (airport, airlines and ATC) from the reference planned/scheduled ATMs) at time (<i>t</i>) (curru/ATM).
$GDP_{0/23}(t) \equiv F_{0/23}(t)$	is the contribution to GDP by the planned/scheduled ATMs at time (<i>t</i>) (curru/ATM).
$CEXT_{0/31} = CD_{0/31}(t) + CN(t)_{0/32} + CAC_{0/33}(t) + CEM_{0/34}(t) \equiv F_{0/31}(t)$	is the total cost of externalities (delays, noise, air traffic incidents/accidents, GHG emissions) of the reference planned/scheduled ATMs at time (<i>t</i>) (curru/ATM).

(cancelled) ATMs, which are internalised as externalities. These indicators of performances in Table 1 are compared to their corresponding reference values given Table 2 for the specified period before the impact of the given disruptive event.

3.4 Models of resilience, robustness, and vulnerability

Analytical models for assessing resilience, robustness and vulnerability of an airport affected by a given disruptive event are based on the loss and savings indicators of performances, the models of which are given in Tables 1 and 2.

3.4.1 Models based on loss indicators of performances

The general theoretical functionality curve and the corresponding polygons based on the loss indicator (*i*) of performance (*j*) used as the figure-of-merit for assessing resilience, robustness and vulnerability of an airport before, during and after the impact of a given disruptive event are shown in Fig. 3 [64].

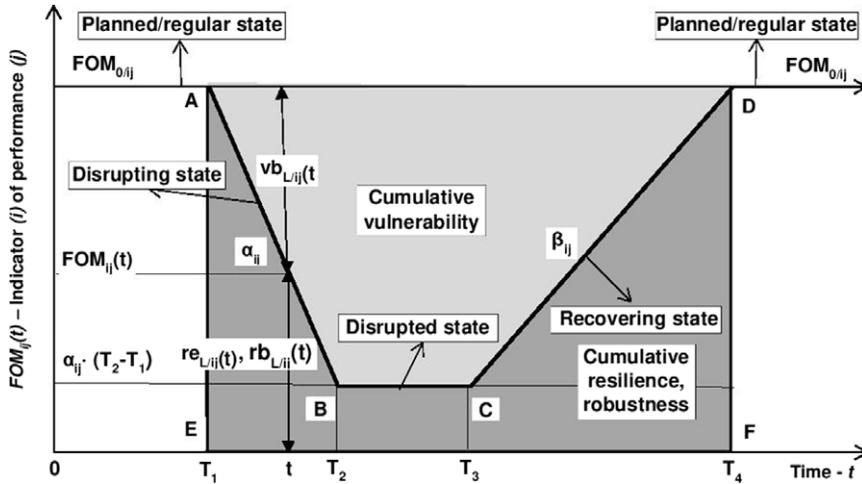


Figure 3. Functionality recovery curve and the corresponding polygons based on loss indicator (*i*) of performance (*j*) as figure-of-merit for estimating resilience, robustness and vulnerability [64].

• Resilience, robustness

Cumulative resilience and robustness of the given airport based on the loss indicator (*i*) of performance (*j*) before, during, and after the impact of the given disruptive event is estimated as the ratio between the darker-shaded part and the total area of the polygon AEFD in Fig. 3 as follows [1, 64]:

$$\begin{aligned}
 RE_{L/ij}(T_4 - T_1) &= RB_{L/ij}(T_4 - T_1) \\
 &= \left[\begin{array}{l} 1, t < T_1 \\ \frac{\int_{T_1}^{T_2} \alpha_{ij} \cdot t dt + \int_{T_1}^{T_4} [FOM_{0/ij} - \alpha_{ij} \cdot (T_2 - T_1)] dt + \int_{T_3}^{T_4} \beta_{ij} \cdot t dt, \text{ for } T_1 < t < T_4 \\ FOM_{0/ij} \cdot (T_4 - T_1) \\ 1, t \geq T_4 \end{array} \right] \\
 &= \left[\begin{array}{l} 1, t < T_1 \\ \frac{\frac{1}{2} \cdot \alpha_{ij} \cdot (T_2 - T_1)^2 + [FOM_{0/ij} - \alpha_{ij} \cdot (T_2 - T_1) \cdot (T_4 - T_1)] + \frac{1}{2} \cdot \beta_{ij} \cdot (T_4 - T_3)^2}{FOM_{0/ij} \cdot (T_4 - T_1)}, \text{ for } T_1 < t \leq T_4 \\ 1, t > T_4 \end{array} \right] \tag{5a}
 \end{aligned}$$

The time-dependent resilience and robustness of the given airport based on the loss indicator (*i*) of performance (*j*) before, during and after the impact of the given disruptive event along the line ABCD in Fig. 3 is estimated as follows [18, 64, 65]:

$$\begin{aligned}
 re_{L/ij}(t) = rb_{L/ij}(t) &= \left[\begin{array}{l} 1, \text{ for } t < T_1 \\ 1 - \frac{\alpha_{ij} \cdot t}{FOM_{0/ij}}, \text{ for } T_1 < t < T_2 \\ 1 - \frac{\alpha_{ij} \cdot (T_2 - T_1)}{FOM_{0/ij}}, \text{ for } T_2 < t \leq T_3 \\ 1 - \frac{\alpha_{ij} \cdot (T_2 - T_1) + \beta_{ij} \cdot t}{FOM_{0/ij}}, \text{ for } T_3 < t \leq T_4 \\ 1, \text{ for } t > T_4 \end{array} \right] \tag{5b}
 \end{aligned}$$

• Vulnerability

The cumulative vulnerability of the given airport based on the loss indicator (i) of performance (j) before, during and after the impact of the given disruptive event is estimated as the ratio between the lighter-shaded area of the polygon ABCD and the total area of the polygon AEFD in Fig. 3 as follows [1, 64]:

$$\begin{aligned}
 VB_{L/ij}(T_4 - T_1) &= \left[\begin{array}{l} 0, t < T_1 \\ \frac{\int_{T_1}^{T_2} \alpha_{ij} \cdot t dt + \int_{T_2}^{T_3} [\alpha_{ij} \cdot (T_2 - T_1)] dt + \int_{T_3}^{T_4} \beta_{ij} \cdot t dt}{FOM_{0/ij} \cdot (T_4 - T_1)}, \text{ for } T_1 < t < T_4 \\ 0, t \geq T_4 \end{array} \right] \\
 &= \left[\begin{array}{l} 0, t < T_1 \\ \frac{\frac{1}{2} \cdot \alpha_{ij} \cdot (T_2 - T_1)^2 + [\alpha_{ij} \cdot (T_2 - T_1) \cdot (T_3 - T_2)] + \frac{1}{2} \cdot \beta_{ij} \cdot (T_4 - T_3)^2}{FOM_{0/ij} \cdot (T_4 - T_1)}, \text{ for } T_1 < t \leq T_4 \\ 0, t > T_4 \end{array} \right] \quad (5c)
 \end{aligned}$$

The time-dependent vulnerability of the given airport based the loss indicator (i) of performance (j) before, during and after the impact of the given disruptive event along the line ABCD in Fig. 3 is estimated as follows [18, 64, 65]:

$$vb_{L/ij}(t) = \left[\begin{array}{l} 0, \text{ for } t < T_1 \\ \frac{\alpha_{ij} \cdot t}{FOM_{0/ij}}, \text{ for } T_1 < t < T_2 \\ \frac{\alpha_{ij} \cdot (T_2 - T_1)}{FOM_{0/ij}}, \text{ for } T_2 < t \leq T_3 \\ 1 - \frac{\alpha_{ij} \cdot (T_2 - T_1) + \beta_{ij} \cdot t}{FOM_{0/ij}}, \text{ for } T_3 < t \leq T_4 \\ 0, t > T_4 \end{array} \right] \quad (5d)$$

where

- i is the loss indicator of performance (j) of the given airport ($i = 1, 2, \dots, N^j$);
- j is the performance of the given airport ($j = 1, 2, \dots, N$);
- N is the number of loss performances of the given airport affected by the given disruptive event;
- N_j is the number of loss indicators of performance (j);
- T_1 is the time when the impact of the indicator (i) of performance (j) starts by the given disruptive event;
- T_2 is the time when the impact of the indicator (i) of performance (j) ends by the given disruptive event;
- T_3 is the time when the recovery of the indicator (i) of performance (j) starts;
- T_4 is the time when the indicator (i) of performance (j) fully recovers;
- t is the time during the observed period;
- $FOM_{0/ij}$ is the reference (planned/regular) value of the loss indicator (i) of performance (j);
- α_{ij} is the rate of deterioration of the loss indicator (i) of performance (j); and
- β_{ij} is the rate of recovery of the loss indicator (i) of performance (j).

In Equation 5(a, c) and (b, d), the cumulative and time-dependent resilience, robustness and vulnerability can vary between 0 and 1 during the observed period (T_1, T_4). They change during the impact of the disruptive event depending on the values of the indicator (i) of performance (j), $FOM_{ij}(t)$ compared to the reference (planned/regular) value $FOM_{0/ij}(T_4 - T_1)$. The value of $FOM_{ij}(t)$ can even be 0 when the given indicator of performance is completely deteriorated. The latter happens when the airport is closed and all flights are cancelled. If the rate of deterioration of the given indicator of performance (α_{ij}) is constant as it is in the given case, the end of deterioration of the corresponding performance will

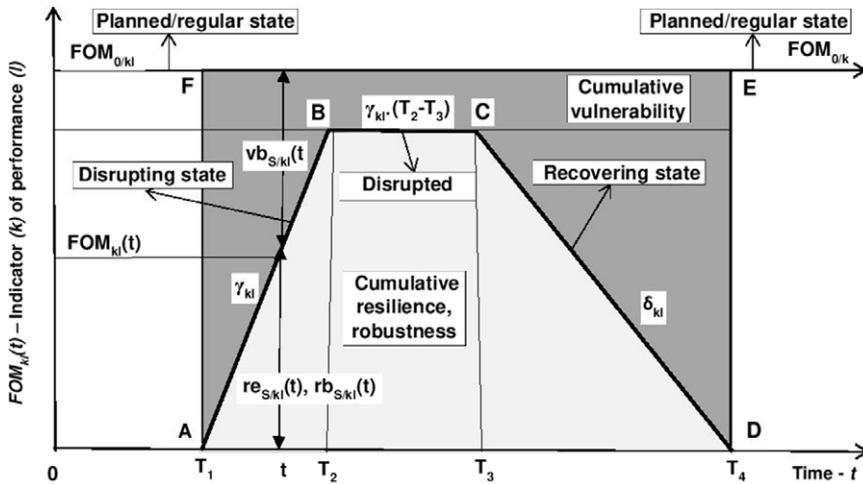


Figure 4. Functionality recovery curve and the corresponding polygons based on savings indicator (*k*) of performance (*l*) as figure-of-merit for estimating resilience, robustness and vulnerability [64].

happen at time: $(T_2 - T_1)$. Consequently, the term $(\alpha_{ij} \cdot t)$ indicates the current value of the deteriorated indicator (*i*) of performance (*j*) at time (*t*) ($t \in T_1, T_2$). For example, this happens when severe weather causes decrease of the airport’s regular/planned capacity and/or the main airlines start to perceive long delays of their flights. In case of a lasting airport closure, all affected flights are cancelled, the indicator (*i*) of performance (*j*) drops to zero, and the corresponding resilience and robustness become minimal and the vulnerability becomes maximal. After reopening of the airport, the indicator (*i*) of performance (*j*) starts to recover due to a rather gradual resumption of the previously cancelled flights. If the recovering rate (β_{ij}) is constant, the time of its full recovery up to the reference (regular/planned) state prior the impact of the disruptive event will be equal to: $T_4 = T_3 + [FOM_{0/ij} - \alpha_{ij} \cdot (T_2 - T_1)] / \beta_{ij}$. In this case, the term $(\beta_{ij} \cdot t)$ represents the restored indicator (*i*) of performance (*j*) at time (*t*) ($t \in (T_3, T_4)$). Consequently, the corresponding resilience and robustness recover towards their full value, while the vulnerability gradually drops to zero.

3.4.2 Models based on savings indicators of performances

The general theoretical functionality recovery curve and the corresponding polygons based on the savings indicator (*k*) of performance (*l*) used as figure-of-merit for estimating resilience, robustness and vulnerability of the given airport before, during and after the impact of the given disruptive event are shown in Fig. 4 [64].

• Resilience, robustness

The resilience and robustness of the given airport based on the savings indicator (*k*) of performance (*l*) before, during and after the impact of the given disruptive event can be quantified as the ratio between the area of the brighter-shaded polygon ABCD and the area of polygon ADEF in Fig. 4 as follows [1, 64]:

$$RE_{S/kl}(T_4 - T_1) = RB_{S/kl}(T_4 - T_1) = \begin{cases} 1, & t < T_1 \\ \frac{\int_{T_1}^{T_2} \gamma_{kl} \cdot t dt + \int_{T_2}^{T_3} \gamma_{kl} \cdot (T_2 - T_1) dt + \int_{T_3}^{T_4} \delta_{kl} \cdot t dt}{FOM_{0/kl} \cdot (T_4 - T_1)}, & \text{for } T_1 < t < T_4 \\ 1, & t \geq T_4 \end{cases}$$

$$= \left[\begin{array}{l} 1, t < T_1 \\ \frac{\frac{1}{2} \cdot \gamma_{kl}(T_2 - T_1)^2 + \gamma_{kl}(T_2 - T_1) \cdot (T_3 - T_2) + \frac{1}{2} \cdot \delta_{kl}(T_4 - T_3)^2}{FOM_{0/kl} \cdot (T_4 - T_1)}, \text{for } T_1 < t < T_4 \\ 1, t \geq T_4 \end{array} \right] \tag{6a}$$

The time-dependent resilience and robustness of the given airport based on the savings indicator (*k*) of performance (*l*) before, during and after the impact of the given disruptive event along the line ABCD in Fig. 3 can be estimated as follows [18, 64, 65]:

$$re_{S/kl}(t) = rb_{S/kl}(t) = \left[\begin{array}{l} 1, \text{for } t < T_1 \\ \frac{\gamma_{kl} \cdot t}{FOM_{0/kl}}, \text{for } T_1 < t < T_2 \\ \frac{\gamma_{kl}(T_2 - T_1)}{FOM_{0/kl}}, \text{for } T_2 < t \leq T_3 \\ \frac{\gamma_{kl}(T_2 - T_1) + \delta_{kl} \cdot t}{FOM_{0/kl}}, \text{for } T_3 < t \leq T_4 \\ 1, \text{for } t > T_4 \end{array} \right] \tag{6b}$$

• Vulnerability

The cumulative vulnerability of the given airport based on the savings indicator (*k*) of performance (*l*) before, during and after the impact of the given disruptive event as the area of the darker-shaded polygon AEFD in Fig. 4 can be quantified as follows [1, 64]:

$$VB_{S/kl}(t) = \left[\begin{array}{l} 0, t < T_1 \\ 1 - \frac{\int_{T_1}^{T_2} \gamma_{kl} \cdot t dt + \int_{T_2}^{T_3} \gamma_{kl} \cdot (T_2 - T_1) dt + \int_{T_3}^{T_4} \delta_{kl} \cdot t dt}{FOM_{0/kl} \cdot (T_4 - T_1)}, \text{for } T_1 < t \leq T_4 \\ 0, t > T_4 \end{array} \right]$$

$$= \left[\begin{array}{l} 0, t < T_1 \\ 1 - \frac{\frac{1}{2} \cdot \gamma_{kl}(T_2 - T_1)^2 + \gamma_{kl}(T_2 - T_1) \cdot (T_3 - T_2) + \frac{1}{2} \cdot \delta_{kl}(T_4 - T_3)^2}{FOM_{0/kl} \cdot (T_4 - T_1)}, \text{for } T_1 < t \leq T_4 \\ 0, t > T_4 \end{array} \right] \tag{6c}$$

The time-dependent vulnerability of the given airport based on the savings indicator (*k*) of performance (*l*) before, during and after the impact of the given disruptive event along the line AEFD in Fig. 3 can be estimated as follows [18, 64, 65]:

$$vb_{S/kl}(t) = \left[\begin{array}{l} 0, \text{for } t < T_1 \\ 1 - \frac{\gamma_{kl} \cdot t}{FOM_{0/kl}}, \text{for } T_1 < t < T_2 \\ 1 - \frac{\gamma_{kl}(T_2 - T_1)}{FOM_{0/kl}}, \text{for } T_2 < t \leq T_3 \\ 1 - \frac{\gamma_{kl}(T_2 - T_1) + \delta_{kl} \cdot t}{FOM_{0/kl}}, \text{for } T_3 < t \leq T_4 \\ 0, \text{for } t > T_4 \end{array} \right] \tag{6d}$$

where

k	is the savings performance of the given airport ($k = 1, 2, \dots, M$);
l	is the indicator of savings performance (k) of the given airport ($k = 1, 2, \dots, M_k$);
M	is the number of savings performances affected by disruptive events;
M_k	is the number of savings indicators of performance (k);
$FOM_{0/kl}$	is the regular/planned value of the savings indicator (k) of performance (l);
γ_{kl}	is the rate of deterioration of the savings indicator (k) of performance (l); and
δ_{kl}	is the rate of recovery of the savings indicator (k) of performance (l).

Other symbols are analogous to those in Equation 5(a–d).

In Equation 6(a, c) and (b, d), the resilience, robustness and vulnerability of the given airport based on the savings indicator (k) of performance (l) can vary between 0 and 1 during the observed period (T_1, T_4). They change during the impact of the disruptive event depending on the values of the indicator (k) of performance (l), $FOM_{kl}(t)$ compared to the reference (planned/regular) value $FOM_{0/kl}$ ($T_4 - T_1$). The value $FOM_{kl}(t)$ can even be 0 when the corresponding indicator is completely deteriorated, i.e. when the maximum savings are made. The latter happens when the airport is closed, all flights are cancelled and consequently not making any costs/externalities. If the rate of reducing the given impact (γ_{kl}) is constant as in the given case, the time of achieving maximum savings in the corresponding indicator (impact) happens after time ($T_2 - T_1$). In addition, the term ($\gamma_{kl} \cdot t$) indicates the current value of the indicator (k) of performance (l) at time (t) ($t \in T_1, T_2$). For example, this happens when the airport's planned regular/capacity decreases due to severe weather and the main airlines start to gradually cancel their planned flights as they expect rather long delays. In the case of airport closure and consequent cancellation of all flights, for example during the period ($T_3 - T_2$), the indicator (k) of performance (l) increases to its maximum reference value $FOM_{0/kl}$. Consequently, the corresponding resilience and robustness will be maximal and the vulnerability minimal. If the recovery of the indicator (k) of performance (l) starts just after the end of the impact of the disruptive event, the time ($T_3 - T_2$) will represent the recovery time. This appears realistic because although the affected airport instantly declares returning to the planned/regular operating regime, the airlines usually need some time to restore the previously long-delayed and/or cancelled flights. If the recovering rate to the full scale of the given impact (δ_{kl}) is constant, the time of full recovery of the given indicator up to its reference value prior to the impact of the disruptive event will be equal to: $T_4 = T_3 + (\gamma_{kl}/\delta_{kl}) \cdot (T_2 - T_1)$. In this case, the term ($\delta_{kl} \cdot t$) represents the restored indicator (k) of performance (l) at time (t) ($t \in T_3, T_4$). Consequently, the corresponding resilience and robustness decrease towards zero and the vulnerability increases to one, i.e. when this savings indicator reaches its reference value as it used to be before the impact of the disruptive event.

4.0 Application of the proposed methodology

4.1 Choice of case airports

The proposed methodology is applied to assess resilience, robustness, and vulnerability of two large airports, LHR (London Heathrow) (UK) and JFK (John F. Kennedy) (US) affected by the COVID-19 pandemic disease during the period January 2020–July 2021. Such airport choice is made in view of the three criteria: (i) size and importance of both airports at the national and international scale connected by one of the world's most profitable airline routes in the year 2019 [66]; (ii) testing the generality of the proposed methodology to be applied to different airports; (iii) indicating the character of impact of the given disruptive event at a rather wide spatial/geographical scale. In addition, the resilience, robustness and vulnerability of the selected airports affected by the given disruptive event are estimated based on the reference average values of particular indicators of performances before its impact started (the year 2019). The costs of impact on the society and environment are internalised as externalities. The inputs and results in the monetary terms are expressed in USDs (US dollar(s)) in order to enable reasonable comparison between both airports.

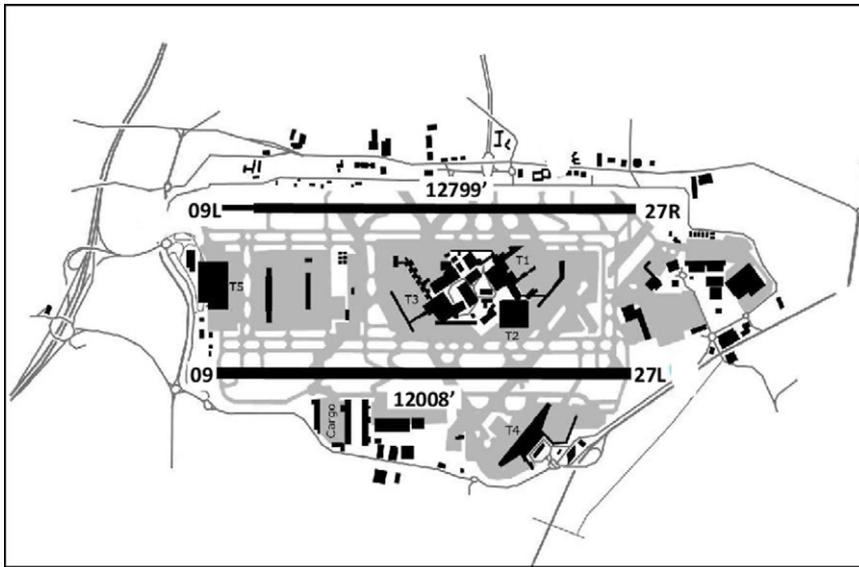


Figure 5. Layout of LHR (London Heathrow) airport [67].

4.2 Inputs

4.2.1 LHR airport

LHR (London Heathrow) airport (UK) is the largest among five London airports (the other four are: Gatwick, Stansted, London City, and London Luton). The scheme of the airport layout is shown in Fig. 5.

Under planned/regular conditions, the airport operates two parallel runways in the segregated mode (one exclusively for arrivals and the other for departures) due to the noise cap of $57 \text{ dBA } L_{eq}$ and $55 \text{ dBA } L_{eq}$ during the day and night, respectively. Consequently, the annual declared runway capacity was $480 \cdot 10^3$ ATMs/year. In the year 2019, LHR airport was connected to 217 destinations – 8 domestic (4%) and 209 international (96%). The average market share of ATMs of three world's regions was about 79%, i.e. North America – 18.3%; Europe (UK, EU, Non-EU) – 50.1%, and Asia Pacific – 10.6% [68]. The market share of three airline alliances – Oneworld, Star Alliance, and SkyTeam – was 84% [69]. In the year 2019, the airport handled: $N_{0/11} = 473 \cdot 10^3$ ATMs, $81 \cdot 10^6$ passengers, and $1.6 \cdot 10^6$ ton of air cargo [67, 70–72].

Table 3 gives the estimated indicators of the above-mentioned performances in the year 2019 relevant for particular actors/stakeholders and used as reference figures-of-merit for assessing resilience, robustness, and vulnerability during the impact of COVID-19 pandemic disease – Period: January 2020–July 2021.

4.2.2 NYC JFK (John F. Kennedy) airport

NYC JFK (John F. Kennedy) airport (US) is the largest among three main New York airports. The other two are LGA (La Guardia), mainly handling domestic, and EWR (Newark International) airport, mainly handling international flights. The simplified airport layout of JFK airport is shown in Fig. 6.

The airport operates two pairs of parallel runways with the annual declared capacity of $735.8 \cdot 10^3$ (84 ATMs/h) (two runways used for arrivals and one for departures) and $788.4 \cdot 10^3$ (90 ATMs/h) (two runways used for departures and one for arrivals). Under planned/regular operating conditions, the airport was connected to 174 destinations: 70 – North America (40%), Europe 30 (17%), and Asia Pacific 16 (9%), which was 66% of the total. In addition, the airline capacity was split to 56.1% domestic and 43.9% international ATMs. The average market share of ATMs of the above-mentioned three regions

Table 3. Indicators of performances as figures-of-merit for assessing resilience, robustness and vulnerability: Case of LHR (London Heathrow) airport (UK)

Indicator	Value ⁽¹⁾
1) Operational performances	
• Flights (ATMs/month) – $N_{0/11} \equiv F_{0/11}$	39,656
Economic performances	
i) Profits	
• Airport (USD/ATM) ⁽²⁾ – $PR_{21/ap} \equiv F_{0/21}$	3,200
– Airlines (USD/ATM) ⁽³⁾ – $\overline{p_{22/ai}}$	1,745
– ATC (USD/ATM) ⁽⁴⁾ – $\overline{p_{23/ATC}}$	45
• Air transport industry (USD/ATM) $PR_{21/ap} + \overline{p_{22/ai}} + \overline{p_{23/ATC}} = PR_{22/ati} \equiv F_{0/22}$	4,990
ii) Contribution to GDP ⁽⁵⁾	
– Number of passengers (pax/ATM) – $\bar{n}_{22/pax}$	170
– GDP1 – $\overline{gdp_{22/1}}$ (USD/pax)	415
– GDP2 – $\overline{gdp_{22/2}}$ (USD/pax)	298
• Total GDP1 (USD/ATM) – $GDP_{0/22/1} \equiv F_{0/23}$	70,525
• Total GDP2 (USD/ATM) – $GDP_{0/22/2} \equiv F_{0/24}$	50,599
3) Social and environmental performances	
i) Delays ⁽⁶⁾	
– Average duration (min/atm) – \bar{w}_{31}	17.5
– Passengers (pax/ATM) – $\bar{n}_{31/pax}$	170
– Average airline cost (USD/min) – $\bar{c}_{31/ai}$	31.7
– Average passenger time cost (USD/pax-min) – $\bar{c}_{31/pax}$	0.955
– Cost of delays (USD/ATM) – $CD_{0/31}$	$17.5 \cdot (0.955 \cdot 170 + 31.7) = 3,396$
ii) Noise (USD/ATM) ⁽⁷⁾ – $CN_{0/32}$	92.5
iii) Incidents/accidents	
– Accident rate (Events/ATM) (Cost of accidents (USD/ATM))	$6.193 \cdot 10^{-66}$ 138.3
– Average cost of accident (USD/ATM) ⁽⁸⁾ – $CAC_{0/33}$	
iv) GHG emissions ⁽⁹⁾	
– Quantity (tonCO _{2e} /ATM) – \bar{q}_n	2.36
– Price (USD/ton/CO _{2e}) – $p_{34/GHG}$	53.3
– Cost of GHG emissions (USD/ATM) – $CEM_{0/34}$	$2.36 \cdot 53.3 = 125.8$
• Total costs/externalities (USD/ATM) $CEXT_{0/31} = CD_{0/31} + CN_{0/32} + CAC_{0/33} + CEM_{0/34} \equiv F_{0/31}$	$3,396 + 2.5 + 138.3 + 125.8 = 3,753$ 3,753

⁽¹⁾Averages – Period: 2019 [73]; ⁽²⁾Average over the period: 2019 (before tax) [71]; ⁽³⁾ Based on 11.14 USD/pax and 170 pax/atm (20 year average) [75]; ⁽⁴⁾ Based on: 13.25 (MTOW/50)^{0.7} (MTOW – Maximum Take-Off Weight) (tons) [78]; ⁽⁵⁾GDP1 – With spending of tourists; GDP2 – Without spending of tourists [75, 76, 77]; ⁽⁶⁾ Refs [67, 71, 74, 79]; GBP = 1.317 USD (GBP – British Pound; USD – US dollar [80]); ⁽⁷⁾ Implies reduction by –3dB during 30 years, 0.1 dB/year or 0.16%/year [67]; ⁽⁸⁾ Heathrow airport: Period: 1962–2018–11 fatal accidents and 17.763·10⁶ ATM; 1 GBP = 1.317 USD [78, 81]; ⁽⁹⁾ Refs [78, 82–85].

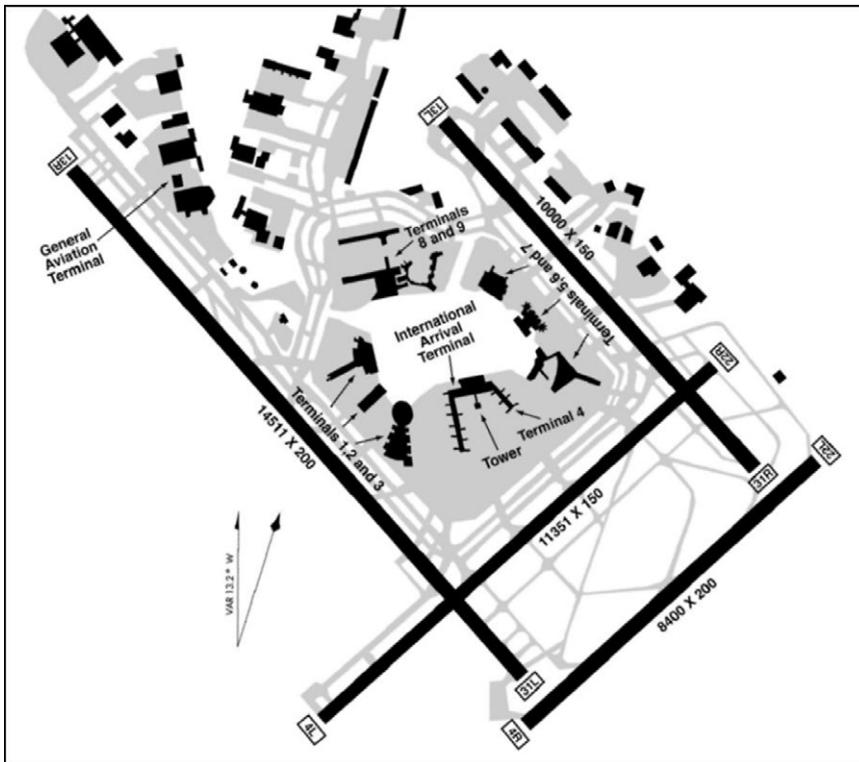


Figure 6. Layout of NYC JFK (John F. Kennedy) airport [86].

was about 88.6%, i.e. North America – 66.6%; Europe-Transatlantic – 18%, and Asia Pacific – 4% [87]. The market share of the three airline alliances – Oneworld, Star Alliance, and SkyTeam – was 64% [88]. In the year 2019, the airport handled: $N_{0/11} = 355.514 \cdot 10^3$ scheduled passenger ATMs, $62.5 \cdot 10^6$ passengers, and $1.4 \cdot 10^6$ ton of air cargo [89, 90]. Table 4 gives the estimated indicators of the above-mentioned performances relevant for particular actors/stakeholders in the year 2019 used as reference figures-of-merit for assessing resilience, robustness and vulnerability during the above-mentioned impact of COVID-19 pandemic disease during the observed period.

4.2.3 Some characteristics of the impact of the given disruptive event

The given disruptive event – the COVID-19 pandemic disease – affected the global air transport system indirectly by requiring almost simultaneously enforcement of various contingency/restrictive measures at the global (national and international) scale. Most measures embraced stricter checking and screening of air passengers at the airports, post travel quarantines, but also completely constraining the access to the airports and airline services. Figure 7 shows the introduction of particular contingency/restrictive measures at the global scale – in the three above-mentioned regions during the observed period (January 2020-March 2021).

As can be seen, in the three above-mentioned regions, North America, Europe and Asia-Pacific, the increased screening (Level 1 measure) of air passengers at airports, quarantining arrivals from the high-risk regions (Level 2 measure) and closing arrivals to/from some regions (Level 3 measure) were successively applied during the first quarter of the year 2020 (until April 2020). With some variations within the same and between different above-mentioned regions, the measures around Level 3 were in place until the end of the observed period. Since under regular operating conditions LHR and NYC JFK

Table 4. Indicators of performances as figures-of merit for assessing resilience, robustness, and vulnerability: Case of NY JFK (John F. Kennedy) airport (US)

Indicators	Value ¹⁾
Operational performance	
• Flights (ATM/month) – $N_{0/11} \equiv F_{0/11}$	29,626
(1) Economic performance	
<i>Profits</i>	
• Airport (USD/atm) ²⁾ – $PR_{21/ap} \equiv F_{0/21}$	1,106
– Airlines (USD/ATM) ³⁾ – $\overline{p_{22/ai}}$	1,736
– ATC (USD/ATM) ⁴⁾ – $\overline{p_{23/ATC}}$	141
• Air transport industry (USD/ATM)	
$PR_{21/ap} + \overline{p_{22/ai}} + \overline{p_{23/ATC}} = PR_{22/ati} \equiv F_{0/22}$	2,983
ii) Contribution to GDP ⁵⁾	
• Total GDP1 (USD/ATM) – $GDP_{0/1} \equiv F_{0/23}$	33,205
• Total GDP2 (USD/ATM) – $GDP_{0/2} \equiv F_{0/24}$	22,168
(2) Social and environmental performance	
i) Delays ⁶⁾	
– Average duration (min/ATM) – \bar{w}_{31}	16.50
– Passengers (pax/ATM) – $\bar{n}_{31/pax}$	176
– Average airline cost (USD/min) – $\bar{c}_{31/ai}$	0.783
– Passenger time cost (USD/pax-min) – $\bar{c}_{31/pax}$	74.24
– Cost of delays (USD/ATM) – $CD_{0/31}$	$16.5 \cdot (176 \cdot 0.783 + 74.24) = 3496$
ii) Noise (USD/ATM) ⁷⁾ – $CN_{0/32}$	
	0
iii) Incidents/accidents (USD/ATM) ⁽⁸⁾	
– Accident rate (events/atm) ⁽⁸⁾ – ACR	$2/7.625 \cdot 10^6$
– Cost of accident (USD/event) – c_{ac}	$87.01 \cdot 10^6$
– Cost of an incident/accident (USD/ATM) – $CAC_{0/33}$	$(2/7.625 \cdot 10^6)/87.01 \cdot 10^6 = 22.8$
iv) GHG emissions ⁹⁾	
– Quantity (tonCO _{2e} /ATM) – \bar{q}_n	2.625
– Price (USD/ton/CO _{2e}) – $p_{41/GHG}$	40.5
– Cost of GHG emissions (USD/ATM) – $CEM_{0/34}$	$2.625 \cdot 40.5 = 106.3$
• Total costs/externalities (USD/ATM)	
$CEXT_{0/31} = CD_{0/31} + CN_{0/32} + CAC_{0/33} + CEM_{0/34} \equiv F_{0/31}$	$3,496 + 0 + 22.8 + 106.3 = 3,625$

⁽¹⁾Averages – Period: 2019 [90]; ⁽²⁾Averages – Period: 2019 (before tax) [91]; ⁽³⁾ Refs [92, 93]; ⁽⁴⁾ Ref. [94]; ⁽⁵⁾ GDP1 – With spending of air visitors; GDP2 – Without spending of air visitors [95–97]; ⁽⁶⁾ Ref. [98]; ⁽⁷⁾ Ref. [99]; ⁽⁸⁾ Period: 2000–2019 [100]; ⁽⁹⁾ Refs. [83–85, 101].

airports had substantial shares of traffic to/from these three regions, contingency/restrictive measures both in these regions and domestically have considerably affected both airports.

4.3 Analysis of results

The resilience, robustness and vulnerability of both airports are estimated in view of the indicators of operational, economic and environmental performances during the observed (disrupting) period (January 2020–June 2021). The indicator of operational performances (the number of ATMs per month), the indicators of economic performances (the airport and aviation industry’s profits per ATM, contribution to GDP per ATM), the indicators of social performances (costs/externalities of delays and

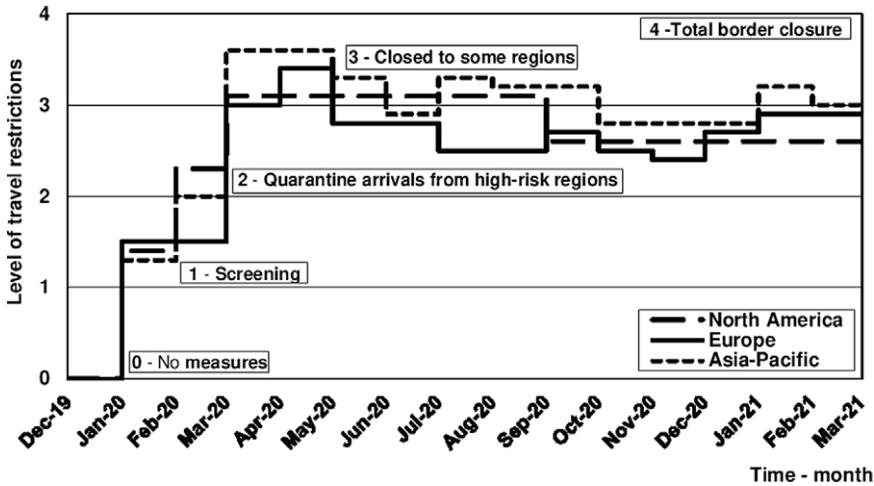


Figure 7. Simplified scheme of introducing contingency/restrictive measures in the air transport system affected by COVID-19 pandemic disease (Period: January 2020-March 2021) [102].

noise, and air traffic incidents/accidents per ATM) and the indicators of environmental performances (costs/externalities of GHG emissions per ATM) are derived from the average reference values in the year 2019. The indicator of social performance – the air traffic incidents/accidents per ATM – is based on the average reference values during the past decade. All above-mentioned indicators of performances estimated under planned/regular operating conditions in the year 2019 are assumed to be the same for the ATMs carried out during the above-mentioned observed (disrupting) period (January 2020–June 2021). This is an assumption, since it was not taken into account that some airlines intentionally operated a certain number of semi-full or almost empty ATMs.

4.3.1 Operational performances

• ATMs (Air Transport Movement(s)) at airports

Figure 8(a, b) shows the number of ATMs (air transport movements) at both airports, representing the loss indicator of their operational performances and the corresponding time-dependent resilience, robustness and vulnerability during the observed (disrupting) period.

Figure 8(a) shows that during the first quarter of the year 2020, the number of ATMs at LHR airport decreased from 35,328 to 4,873 ATMs (−86%). During the same period, the number of ATMs at NYC JFK airport decreased from 27,235 to 3,125 ATMs (−89%). During the next six months (period: April–October 2020), the number of ATMs at LHR airport gradually increased to 18,026 ATMs (−50%) and at NYC JFK airport to 10,790 ATMs (−40%). Later on, during the following five months (period: October 2020–February 2021) the number of ATMs at LHR again decreased to 7,785 (−78%). During the same period, the number of ATMs at NYC JFK airport increased to 11,516 ATMs (− 61%). Furthermore, during the period February–June 2021, the number of ATMs increased at both airports – to 13,255 ATMs (− 62%) at LHR and 24,779 ATMs (−16%) at NYC JFK airport.

Figure 8(b) shows that at the beginning of the observed period (the first quarter of the year 2020), the resilience and robustness of both airports were sharply decreasing during March 2020 and reached their minimum in April 2020 of about: $re_{LJI}(4) = rb_{LJI}(4) \approx 0.10$ (i.e. 10%) compared to the reference value of: $re_{LJI}(0) = rb_{LJI}(0) = 1.0$ (i.e. 100%) in the year 2019. The rate of their decrease was about: $\alpha_{LJI} \approx 22.5\%$ /month. Consequently, the vulnerability of both airports was increasing at approximately the same rate: $\beta_{LJI} = 22.5\%$ /month and reached its maximum in April 2020 at about: $vb_{LJI}(4) \approx$

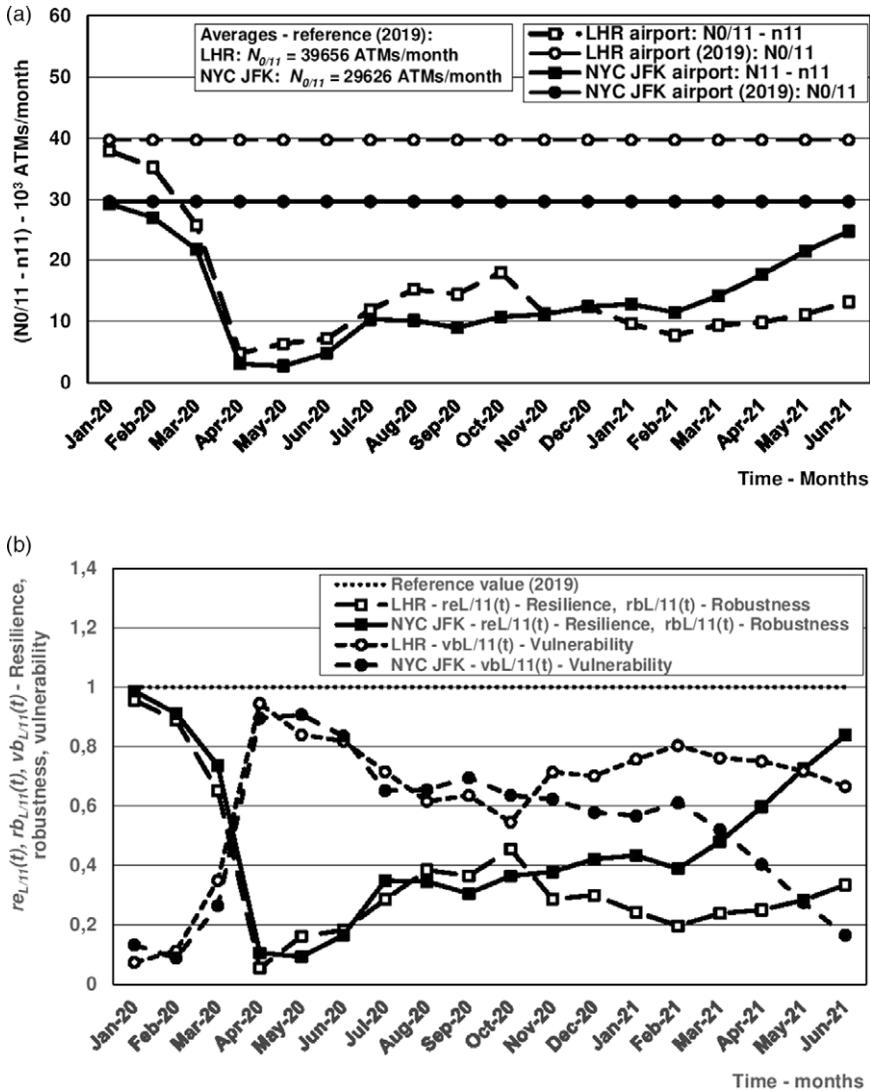


Figure 8. Operational performances – Number of ATMs (Air Transport Movement(s)): Case of LHR (London Heathrow) and NYC JFK (John F. Kennedy) airport – Impact of COVID-19 pandemic disease (Period: January 2020–July 2021). (a) Time-dependent number of ATMs, (b) Time-dependent functionality – resilience, robustness and vulnerability.

0.90–0.95 (i.e. 90%–95%). Such developments were mainly driven by an increased impact of the COVID-19 disease, which increasingly prevented the access of air passengers to the airports and airlines there. For example, at the beginning of March, the dominant airline, British Airways, cancelled most of its international short-haul (UK and European) and long-haul intercontinental flights at LHR airport. At the same time, foreign airlines from similarly affected countries cancelled most of their medium-haul (continental European) and long-haul intercontinental flights to LHR airport (the UK and most of these countries were under conditions of full or close-to-full lock-down) [103]. At the same time, NYC JFK airport was also affected by different forms of impact of the COVID-19 pandemic disease. One was the US travel restrictions imposed on 26 European countries (announced on 12 March 2020). Airlines such as Lufthansa and Air France-KLM had to cancel their flights between the above-mentioned European (Schengen area) countries and the US, including those to/from NYC JFK airport. Flights from the UK

and Ireland were exempted. The other form was the COVID-19 pandemic infection of the staff at 17 US ATC control centres including that of the NYC (New York City) area. Consequently, American Delta and United airlines cancelled about 90% of their domestic and international short-haul, medium-haul, and long-haul flights to/from the increasingly affected New York City area, including that to/from NYC JFK airport. On the contrary, JetBlue airline tried to consolidate its presence there under the given conditions [104, 105].

Later on, due to the partial relaxation of access conditions to air transport services, the resilience and robustness of LHR airport were recovering during the sub-period April–October 2020 at an average rate of: $\beta_{L11} \approx 5.8$ %/month up to the level: $re_{L11}(10) = rb_{L11}(10) \approx 0.45$ (i.e. 45%). However, with the repeated tightening of the access-restrictive measures, the resilience and robustness were deteriorating over the sub-period October 2020–February 2021 at the rate of: $\alpha_{L11} \approx 6.25$ %/month to about: $re_{L11}(14) = rb_{L11}(14) \approx 0.20$ (i.e. 20%). Finally, with further relaxation of the access-restrictive measures, the resilience and robustness were recovering again during the last sub-period February–June 2021 at the rate of: $\beta_{11} \approx 3.25$ %/month to the level: $re_{L11}(18) = rb_{L11}(18) \approx 0.33$ (i.e. 33%). The corresponding vulnerabilities at the end of the above-mentioned sub-periods were: $vb_{L11}(10) \approx 0.55$ (i.e. 55%), $vb_{L11}(14) \approx 0.80$ (i.e. 80%), and $vb_{L11}(18) \approx 0.67$ (i.e. 67%), respectively.

The resilience and robustness of NYC JFK airport over the sub-period April 2020–February 2021 were also recovering due to the relaxation of demand-access restrictions mainly throughout the US. The resilience and robustness were recovering with some rather slight variations at an average rate of: $\beta_{11} \approx 3$ %/month from the level: $re_{L11}(4) = rb_{L11}(4) \approx 0.09$ (i.e. 9%) to the level: $re_{L11}(14) = rb_{L11}(14) \approx 0.39$ (i.e. 39%), and again during the sub-period February 2021–June 2021 at the rate of: $\beta_{11} \approx 11.25$ %/month to the level: $re_{L11}(18) = rb_{L11}(18) \approx 0.84$ (i.e. 84%) by the end of the observed period (June 2021). The corresponding vulnerabilities at the end of the above-mentioned sub-periods were: $vb_{L11}(14) \approx 0.61$ (i.e. 61%) and $vb_{L11}(18) \approx 0.16$ (i.e. 16%), respectively.

The total number of ATMs, which would have been carried out at LHR and NYC JFK airports under planned/regular operating conditions during the observed period (January 2020–June 2021), would be: $N_{011} = 713,808$ and $N_{011} = 533,268$ ATMs, respectively (based on the average reference monthly number in the year 2019 of: $N_{011} = 39,656$ ATM/month at LHR and $N_{011} = 29,626$ ATM/month at NYC JFK airport). The actual number of cancelled ATMs during the same period was: $n_{11} = 459,910$ ATMs at LHR and $n_{11} = 280,917$ ATMs at NYC JFK airport. Consequently, the cumulative resilience, robustness and vulnerability of LHR airport were: $RE_{L11}(1,18) = RB_{L11}(1,18) = 0.356$ and $VB_{L11}(1,18) = 0.644$, respectively. Those of NYC JFK airport were: $RE_{L11}(1,18) = RB_{L11}(1,18) = 0.473$ and $VB_{L11}(1,18) = 0.527$. These indicate that the robustness and resilience of NYC JFK airport were higher than their counterpart values for LHR airport by about 33%. The vulnerability of LHR airport was higher than that of NYC JFK airport by about 22%. This indicated that under the given conditions the resilience and robustness of NYC JFK airport were higher and the vulnerability was lower than that of LHR airport by about 33% and 20%, respectively.

4.3.2 Economic performances

• Airport and aviation industry's profits

Figure 9(a, b) shows the time-dependent and cumulative profits of both airports and related aviation industries as the loss indicators of economic performances during the observed (disrupting) period (January 2020–June 2021). Since these profits directly depend on the number of ATMs, the corresponding time-dependent resilience, robustness, and vulnerability are not explicitly shown because they are equivalent to those based on the number of ATMs.

Figure 9(a) shows that the airport and aviation industry's profits were substantively affected by the cancellation of ATMs at both airports and actually changed in line with the changes of the cancelled ATMs during the observed period. As can be seen, the losses of profits of LHR airport and the related aviation industry were maximal in April 2020, -111.3 and -173.6 million USD, respectively, and again in February 2021, 125.4 and 194 million USD, respectively. In the meantime, they were following the changes of the cancelled ATMs. In addition, the maximum losses of profits of NYC JFK airport and

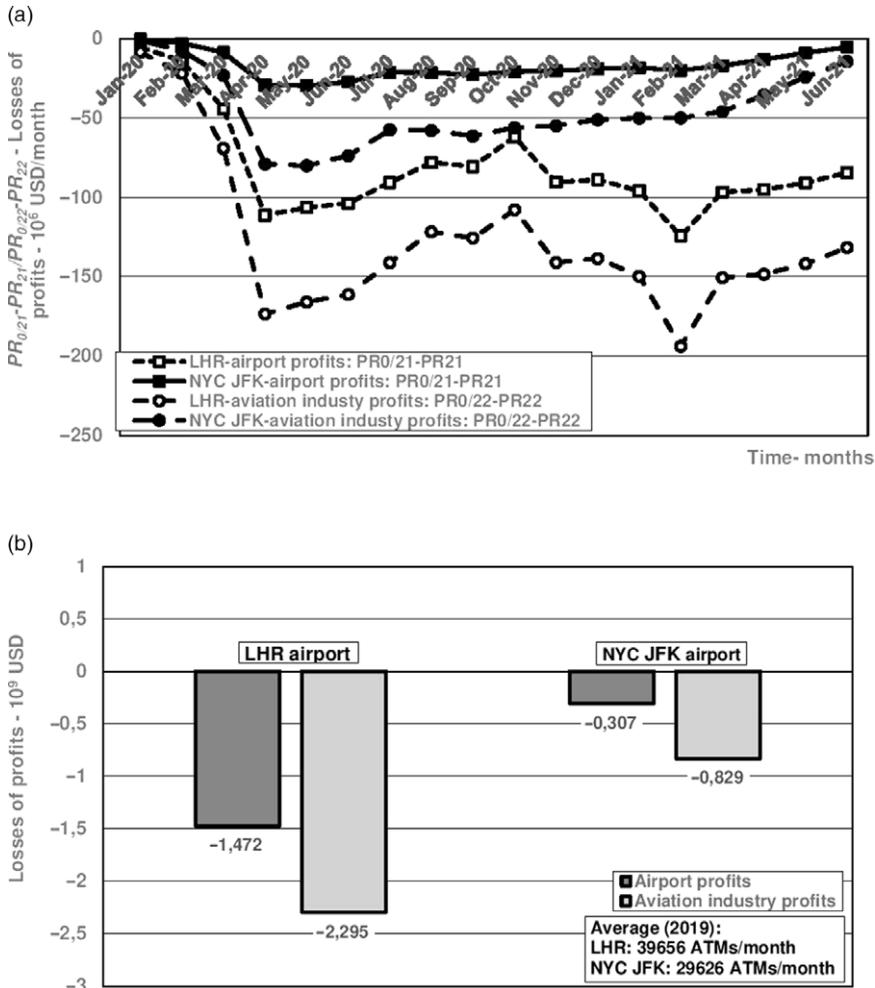


Figure 9. Economic performances – Airports and aviation industries’ profits: Case of LHR (London Heathrow) and NYC JFK (John F. Kennedy) airport – Impact of COVID-19 pandemic disease (Reference period: Average month in 2019; Period: January 2020 – July 2021). (a) Time-dependent profits of airports and related aviation industries, (b) Cumulative losses of profits of airports and aviation industries.

the aviation industry there were also incurred in April 2020, -29.3 and 79.0 million USD. During the remainder of the observed period, these profits were gradually increasing due to the recovering number of ATMs. Figure 9(b) shows that cumulative losses of airport and aviation industry’s profits of LHR airport were about -1.47 and -2.3 billion USD, respectively, and those of NYC JFK airport about -0.31 and -0.83 billion USD, respectively. The cumulative resilience, robustness, and vulnerability of LHR airport and the aviation industry during the observed period were the same as those of ATMs: $RE_{L21/22}(1,18) = RB_{L21/22}(1,18) = 0.356$ and $VB_{L21/22}(1,18) = 0.644$, respectively. Those of NYC JFK airport were: $RE_{L21/22}(1,18) = RB_{L21/22}(1,18) = 0.479$ and $VB_{L21/22}(1,18) = 0.521$.

• **Contribution to GDP**

Figure 10(a, b) shows the time-dependent and cumulative contribution to GDP (Gross Domestic Product) as the loss indicators of economic performances during the observed (disrupting) period

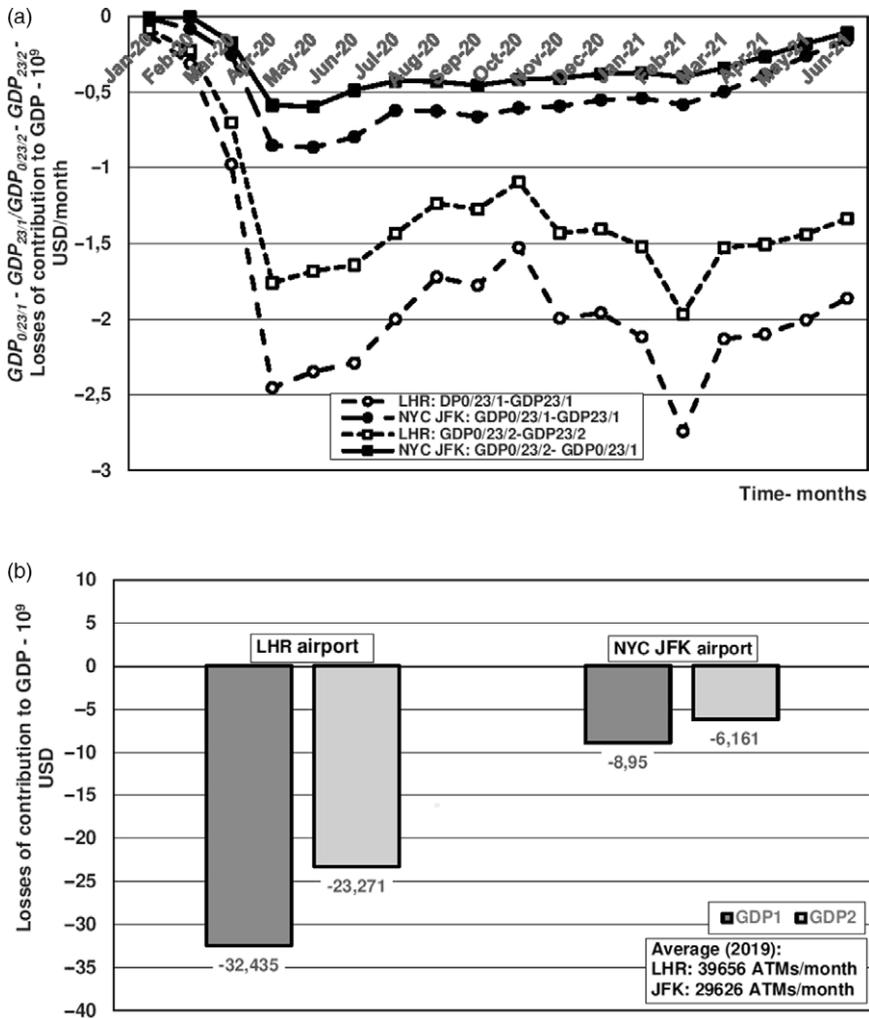


Figure 10. Economic performances – Contribution to GDP (Gross Domestic Product): Case of LHR (London Heathrow) and NYC JFK (John F. Kennedy) airport (GDP1 – With spending of tourists/air visitors; GDP2 – Without spending of tourists/air visitors) – Impact of COVID-19 pandemic disease (Reference period: Average month 2019; Period: January 2020–July 2021). (a) Time-dependent contribution to GDP, (b) Cumulative losses of contribution to GDP.

(January 2020–June 2021). As in the case of airport and aviation industry’s profits, the corresponding time-dependent resilience, robustness and vulnerability are not explicitly shown since they are again equivalent to those based on the number of ATMs.

Figure 10(a) shows that the contribution of both airports to GDP was changing in line with the changes in the number of cancelled ATMs during the observed period. The maximum losses of the contribution by LHR airport were in April 2020 (GDP1 – 2.45 billion USD with spending of tourists and GDP2 – 1.76 billion USD without spending of tourists) and again in February 2021 (GDP1 – 2.74 billion USD with spending of tourists and GDP2 – 1.97 billion USD without spending of tourists). The maximum losses of the contribution by NYC JFK airport were in April 2020 (GDP1 – 0.85 billion USD with spending of air visitors and GDP2 – 0.59 billion USD without spending of air visitors). During the rest of the observed period (until June 2021), the losses of contribution to GDP were decreasing due to the gradual decrease in the number of cancelled ATMs. Figure 10(b) shows that the cumulative losses of contribution to GDP

during the observed period (January 2020–June 2021) by LHR airport were –32.4 billion USD (GDP 1 with spending of tourists) and –23.4 billion USD (GDP2 without spending of tourists). Those by NYC JFK were –8.95 and –6.16 billion USD, respectively. The corresponding cumulative resilience, robustness and vulnerability of both airports were similar to those in the case of losses of profits of the airports and related aviation industries, i.e. for LHR airport: $RE_{L/23}(1,18) = RB_{L/23}(1,18) = 0.356$ and $VB_{L/23}(1,18) = 0.644$, respectively, and for NYC JFK airport: $RE_{L/23}(1,18) = RB_{L/23}(1,18) = 0.479$ and $VB_{L/23}(1,18) = 0.521$.

4.3.3 Environmental and social performances

• Costs/externalities

Figure 11(a, b, c) shows the time-dependent and cumulative costs/externalities, representing the savings indicator of social and environmental performances and the corresponding cumulative resilience, robustness, and vulnerability of both airports during the observed (disrupting) period.

Figure 11(a) shows that the monthly savings in the costs/externalities were generally higher at LHR than at NYC JFK airport and changed in line with the number of cancelled ATMs during the entire observed period. The main reasons for such difference were the higher number of cancelled ATMs at LHR airport and the higher average costs/externalities per atm. The highest positive difference in favour of LHR airport of about 49% was at the end of the first quarter of the observed period (April 2020) and then again about 147% at the end of the half of the first quarter in 2021 (February 2021). After that time, the positive gap in favour of LHR airport was continuously increasing by the end of the observed period, and it was mainly driven by the higher rate of recovering ATMs at NYC airport. Figure 11(b) shows that the cumulative savings in cost/externalities were by about 99% higher at LHR than at NYC JFK airport during the observed period. Figure 11(c) shows that the corresponding cumulative resilience, robustness and vulnerability were different at both airports. In the given context, LHR airport was more resilient and consequently less vulnerable than NYC airport under the given conditions by about 19% and 28.5%, respectively.

4.3.4 Net impact

Figure 12 shows the total differences between the losses of airport and aviation industry's profits and the corresponding contribution to GDP, and the savings in the costs/externalities of both airports impacted by the given disruptive event – COVID-19 pandemic disease during the observed period (January 2020–June 2021).

As can be seen, these total losses in range of billions of USD were about 4 times higher at LHR than at NYC JFK airport during the observed period. This indicates that generally the savings in costs/externalities based on the current charging of corresponding impacts can only marginally compensate for overall losses of benefits from the cancelled ATMs at the given airports under given conditions.

4.3.5 Some causes of differences in the impact of the same disrupting event between airports

The above-mentioned airport characteristics and the applied contingency/restrictive measures shown in Fig. 7 could be used to explain the differences in the indicators of considered performances and related resilience, robustness and vulnerability of both airports affected by the COVID-19 pandemic disease. The main reasons for these differences are summarised as follows:

- The number of planned/regular and cancelled ATMs at LHR were higher by about 33% and 64% than that at NYC JFK, respectively.
- The average airport and aviation industry's profits and contribution to GDP per ATM were about 2.9, 1.67, 2.18 (GDP1), and 2.39 (GDP2) times higher at LHR than their counterpart values at

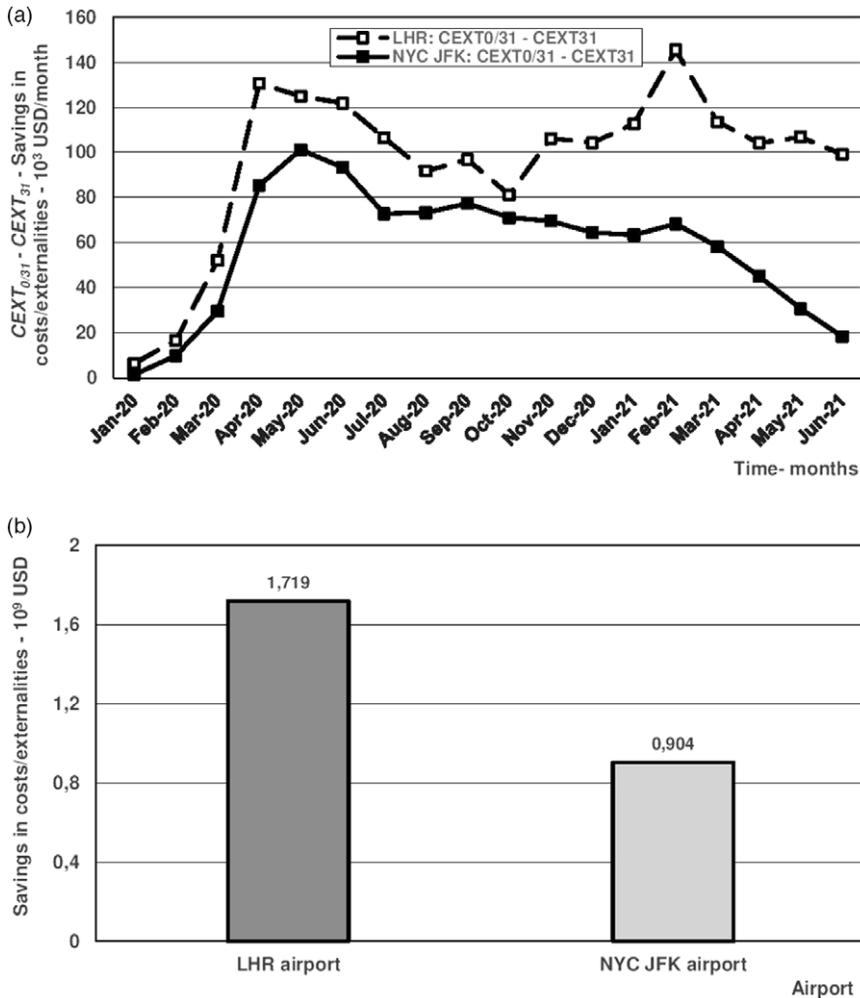


Figure 11. Social and environmental performances – Costs/externalities: Case of LHR (London Heathrow) and NYC JFK (John F. Kennedy) airport – Impact of COVID-19 pandemic disease (Reference period: Average month 2019; Period: January 2020–July 2021. (a) Time-dependent savings in costs/externalities, (b) Cumulative savings in costs/externalities, (c) Cumulative resilience, robustness and vulnerability.

NYC JFK airport, respectively. The average costs/externalities per ATM were about 1.15 times higher at LHR than those at NYC JFK airport.

- Based on the differences in the total number of planned/regular and cancelled ATMs and differences in the averages per ATM, the total airport and aviation industry’s profits and contribution to GDP were about 4.8, 2.8, 3.6 (GDP1) and 3.8 (GDP2) times higher at LHR than their counterpart values at NYC JFK airport, respectively, during the observed period. The total costs/externalities per atm were higher about 1.90 times at LHR than that at NYC JFK airport.
- At both airports, the given disruptive event had a very similar strong impact during the first quarter of the observed period (January–April 2020). During the rest of the observed period, the nature of the impact was different at both airports. Due to the predominantly international ATMs (92%–94%), LHR airport remained highly dependent on the above-mentioned contingency/restrictive measures in the three regions rather than on the measures at the local (UK)

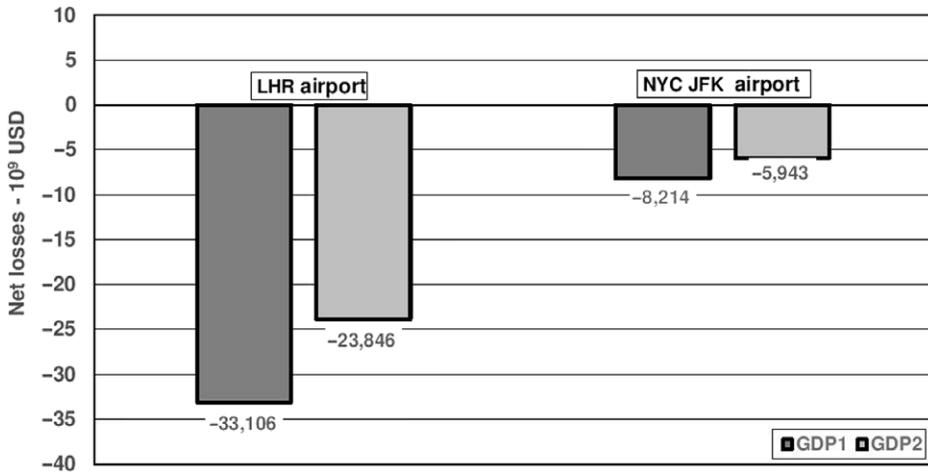


Figure 12. Differences between the total losses of profits and contributions to GDP and the total savings in costs/externalities: Case of LHR (London Heathrow) and NYC JFK (John F. Kennedy) airport – Impact of COVID-19 pandemic disease (Period: January 2020–July 2021).

scale. Most of the contingency/restrictive measures remained around Level 3, thus causing a slow, modest, and rather fluctuating recovery of the airport ATMs. Thanks to the relaxation of the US contingency/restrictive measures, NYC JFK airport with its generally substantive share of domestic ATMs (66.6%) was modestly but continuously recovering by the end of the observed period. Such recovery was contributing to decreasing losses of the airport and aviation industry’s profits and contributions to GDP on the one hand, and reducing savings in the costs/externalities on the other.

5.0 Conclusions

Airports were frequently exposed to impacts of different disruptive events, which generally affected their planned/regular operational, economic, social, and environmental performances. Under such conditions, the ability to withstand and maintain a certain level of functionality of performances indicated resilience, the degree of resisting the disruptive impact indicated robustness, and the scale of impaired functionality of performances caused by the disruptive events indicated vulnerability of these airports. In general, disruptive events frequently caused long delays and cancellations of airline flights (ATMs – Air Transport Movement(s)). In particular, cancellation of ATMs affected operational and consequently economic performances of main actors/stakeholders involved, in terms of losses of profits of the affected airports, aviation industry (airports, airlines, ATC) and contribution to GDP (Gross Domestic Product) of the society. At the same time, they also contributed to savings in the costs of impacts on the society and environment, i.e. the externalities.

This paper develops a methodology for assessing resilience, robustness, and vulnerability of airports affected by the given disruptive event. The methodology consists of analytical models of indicators of particular performances and analytical models for assessing resilience, robustness, and vulnerability using these indicators as figures-of-merit under given conditions.

The methodology is applied to two large airports – LHR (London Heathrow, UK) and NYC JFK (John F. Kennedy, US), affected by a global large-scale disruptive event – the COVID-19 pandemic disease during the period January 2020–June 2021. A substantive number of ATMs was cancelled and it consequently directly influenced the operational, economic, social, and environmental performances of both airports during the observed period. At LHR airport, it was 459,910 vs 713,808 ATMs and at NYC JFK it was 280,917 vs 533,268 ATMs.

The consequent cumulative losses of the airport and aviation industry's profits at LHR airport were about -1.47 and -2.3 billion USD, respectively, and those at NYC JFK airport about -0.31 and -0.83 billion USD, respectively. The cumulative losses of contribution to GDP by LHR airport were -32.4 billion USD (GDP 1 with spending of tourists) and -23.4 billion USD (GDP 2 without spending of tourists). Those by NYC JFK were -8.95 billion USD (GDP1 with spending of air visitors) and -6.16 billion USD (GDP2 without spending of air visitors), respectively. Regarding the above-mentioned indicators of performances, the cumulative functionality, i.e. resilience and robustness of LHR airport were 0.356 and the vulnerability was 0.644. Those of NYC JFK airport were 0.473 and 0.527, respectively. This indicated that under the given conditions the resilience and vulnerability of NYC JFK airport were higher and the vulnerability was lower than that of LHR airport by about 33% and 20%, respectively.

The cumulative savings in costs/externalities were 1.719 billion USD at LHR and 0.904 billion USD at NYC JFK airport. The corresponding cumulative resilience, robustness, and vulnerability of LHR airport were 0.642 and 0.358, respectively. Those of NYC JFK airport were 0.540 and 0.460, respectively. LHR airport was more resilient and consequently less vulnerable than NYC airport under the given conditions by about 19% and 28.5%, respectively. The total cumulative losses in the range of billions of USD were about 4 times higher at LHR (-33.106 and -23.846 billion USD) than at NYC JFK (-8.214 and -5.943 billion USD) airport during the observed period. This indicates that generally the savings made in costs/externalities based on the current charges for the corresponding impacts could not substantively compensate for the overall losses of benefits – profits and contributions to GDP of the actors/stakeholders involved – from the cancelled ATMs during the observed period under the given conditions.

Further research could deal with the following topics:

- Investigating the influence of air cargo demand and capacity component on particular indicators of performances and their application as figures-of-merit for assessing resilience, robustness and vulnerability of considered airports under given disruptive conditions;
- Developing scenarios of full recovery of affected airports and estimating total prospective losses/benefits of actors/stakeholders caused by the impact of a given disruptive event under given conditions;
- Developing more detailed analytical models of indicators of particular performances and their potential interrelationships;
- Testing the generality of the proposed methodology to be applied to other airports affected by different disruptive events.

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