Critical Airport Infrastructure Disaster Resilience: A Framework and Simulation Model for Rapid Adaptation

Comes, Tina; Warnier, Martijn; Feil, Wouter; van de Walle, Bartel

DOI
10.1061/(ASCE)ME.1943-5479.0000798

Publication date
2020

Document Version
Final published version

Published in
Journal of Management in Engineering

Citation (APA)
Comes, T., Warnier, M., Feil, W., & van de Walle, B. (2020). Critical Airport Infrastructure Disaster Resilience: A Framework and Simulation Model for Rapid Adaptation. *Journal of Management in Engineering*, *36*(5), Article 04020059. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000798

Critical Airport Infrastructure Disaster Resilience: A Framework and Simulation Model for Rapid Adaptation

Tina Comes, Ph.D.[1]; Martijn Warnier, Ph.D.[2]; Wouter Feil[3]; and Bartel Van de Walle, Ph.D.[4]

Abstract: Resilient critical airport infrastructures affected by a disaster need to sustain minimal functionality and quickly resume full operation, while at the same time coping with the increased operational demands imposed by the unfolding disaster response. In this paper, we develop a resilience framework and model-driven approach that focuses on the ability of the infrastructure to rapidly adapt to a new steady state under these conditions. This requires both the extension of capacity as well as the adaptation of key processes. Through discrete event simulations, we study the implications of different policies to improve airport resilience under different disaster impact scenarios for a stylized case. Our results show that although decision-makers may be tempted to focus on short-term measures that can be implemented immediately, resilience is improved most by a combination of rapid process changes and longer-term measures that structurally increase airport capacity. **DOI: 10.1061/(ASCE)ME.1943-5479.0000798.** *© 2020 American Society of Civil Engineers.*

Introduction

Critical infrastructures are essential for our society's prosperity and quality of living. Yet, with the increasing frequency and severity of climate change–induced extreme weather events, critical infrastructures, especially in low- and middle-income countries, are increasingly prone to failure leaving millions without essential supplies such as food, water, or health care (Hallegatte et al. 2019). Not surprisingly, resilience is increasingly viewed as a key design principle and policy imperative with the objective to ensure that a critical infrastructure affected by a major disruption can sustain minimal functionality and resume full operation quickly and safely (Bruneau et al. 2003).

In the aftermath of a disaster, critical hub infrastructures are vital for the recovery of the affected region (Hallegatte et al. 2019; Comes and de Walle 2014). For example, seaports may receive more incoming shipments for reconstructing damaged areas, or hospitals may have to cater for more injured patients. As such, the critical hub infrastructure not only needs to resume its predisaster level of performance, but may at the same time have to deal with, and provide for, a significantly increased operational load.

In this paper, we elaborate on the case of airports as a critical hub infrastructure. A disaster has typically two immediate effects on an airport. First, the disaster at least partially disrupts the airport function and reduces its capacity. Second, in response to the disaster, the airport finds itself in a new role as a disaster relief logistics hub. This new role comes with an increase of incoming aircrafts bringing supplies or aid workers. For an airport already struggling to regain its normal capacity, this additional load often creates congestion with significant bottlenecks at the airport hampering the ensuing response (Holguín-Veras et al. 2012; Veatch and Goentzel 2018).

Therefore, we propose an approach for measuring critical infrastructure resilience that includes the rapid adaptation of critical infrastructure systems to new performance requirements brought about by a disaster. We formalize this approach to resilience by means of three key characteristics: absorption capacity, adaptive capacity, and the rapidity of adaptation. This resilience concept can be used where resilience entails adaptation of the infrastructure system to meet new unplanned service levels within a relatively short time. Because adaptation entails both an extension of capacity and a change of processes, we use a discrete event simulation to model and measure the infrastructure resilience. We then apply our approach to a stylized disaster case, considering four impact scenarios and six policies to improve resilience. The results of our simulation-driven approach allow us: (1) to gain insights into adaptation of processes at airports during the immediate response phase, (2) to reveal the interaction of system components and processes, and (3) to design and evaluate policies that improve resilience. Lastly, we discuss the validity of our results, and conclude with a brief discussion and future outlook of our approach.

Resilience and Rapid Adaptation Framework

Although the origins of the concept of resilience lie within ecology (Holling 1973), today resilience is used in a wide range of domains, ranging from cities and urban resilience (Meerow et al. 2016; Comes 2016b), communities and their connections (Aldrich and Meyer 2015), to critical infrastructures. Increasingly, resilience also receives attention in the transportation and logistics literature generally (Heckmann et al. 2015; Mattsson and Jenelius 2015).

Traditionally resilience of infrastructures is defined as the ability to rapidly recover from performance losses owing to a disruption (Bruneau et al. 2003). Herein, resilience is understood as a threefold concept: (1) the capacity to absorb a shock or disturbance; (2) the capacity to adapt to change; and (3) the rapidity of the

[1]Associate Professor, Faculty of Technology, Policy, and Management, Dept. of Engineering Systems and Services, Delft Univ. of Technology, Jaffalaan 5, 2628BX Delft, Netherlands (corresponding author). ORCID: https://orcid.org/0000-0002-8721-8314. Email: t.comes@tudelft.nl

[2]Associate Professor, Faculty of Technology, Policy, and Management, Dept. of Multi-Actor Systems, Delft Univ. of Technology, Jaffalaan 5, 2628BX Delft, Netherlands. Email: m.e.warnier@tudelft.nl

[3]Researcher, Faculty of Technology, Policy, and Management, Delft Univ. of Technology, Jaffalaan 5, 2628BX Delft, Netherlands. Email: wouterfeil@gmail.com

[4]Full Professor, Faculty of Technology, Policy, and Management, Dept. of Multi-Actor Systems, Delft Univ. of Technology, Jaffalaan 5, 2628BX Delft, Netherlands. Email: b.a.vandewalle@tudelft.nl

Note. This manuscript was submitted on August 14, 2019; approved on February 5, 2020; published online on June 22, 2020. Discussion period open until November 22, 2020; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Management in Engineering***, © ASCE, ISSN 0742-597X.

recovery process (Francis and Bekera 2014; Mattsson and Jenelius 2015). Over the last two decades many studies have focused primarily on a rapid recovery to a predisaster state (Cimellaro et al. 2010; Comes and de Walle 2014; Janić 2015; Zobel 2011; Ilbeigi and Dilkina 2018). A comprehensive recent review by (Hosseini et al. 2016) provides an overview of applications and adaptations on this initial model.

One of the most important recent shifts in resilience engineering is the recognition that critical infrastructures are complex socio-technical systems and as such need to combine core concepts of engineering resilience [robustness, rapidity, resourcefulness, and redundancy (Zobel 2011; Zio 2016)] with the concepts of adaptation and transformation from social-ecological resilience (Elmqvist et al. 2019). Zio (2016) argues that in particular the long infrastructure life cycles require flexibility and adaptiveness to be part of system design. Reflecting the different timescales of rapid response and longer-term transformation, Woods (2015) distinguishes short-term graceful extensibility (as opposed to brittleness) and longer-term adaptiveness.

The recently proposed stress-strain model (Choi et al. 2019) focuses on this concept of extensibility and presents a resilience framework that captures the need to expand infrastructure capacity during a shock. The authors focus on serviceability as the ability of "an infrastructure system to provide a pre-disaster level of service in a post-disaster situation" (Choi et al. 2019). While this approach allows policy-makers to consider increased demand, it assumes that processes during crises do not change. Therefore, increased demand needs to be met via extra capacity or resources (Woods et al. 2014). However, several studies in disaster research literature have shown that system behavior in disasters is fundamentally different from day-to-day operations (Turoff et al. 2004; Comes 2016a). Similarly, the difference between inherent and adaptive resilience has been stressed previously (Rose 2007), where the latter refers to behavioral change, improvisation, and creativity. Thus far, however, this behavioral change and the different systems' behavior is not considered in the literature on infrastructure resilience.

In air transportation more specifically, most papers focus on resilience of the airline transportation network, mostly by analyzing the underlying complex networks, (Dunn and Wilkinson 2016; Cook et al. 2015; Lordan et al. 2014; Clark et al. 2018). Here, mitigation measures largely relate to rescheduling and rerouting flights (Janić 2015; Cardillo et al. 2013). In addition, most of these papers focus on network disruptions, not on the impact of a large-scale event on airport resilience (Janić 2015), that fundamentally change the flight patterns. Few papers focus on the airport system itself, as a critical hub in the disaster response phase. Malandri et al. (2017) present a model of ground level accessibility, measuring the impact of disruptions in the passenger flow at the airport, and defining resilience as the ability to rapidly recover system performance to baseline levels with respect to passenger delays, inconvenience, and overcrowding. Faturechi et al. (2014) present an optimization model for the rapid recovery of the airport runway and taxi system after disruptions. What is thus missing is a paper that takes into account the need for adaptation and expansion in response to a disaster that focuses on the airport system as a critical hub infrastructure.

This paper addresses the gap by explicitly considering the rapid change of process and systems behavior during the response to a crisis by following a two-fold approach. First, we propose a resilience framework that is designed to take into account rapid adaptation of system behavior that is required to meet the significantly higher performance levels as compared to predisaster operations. Second, we capture systems behavior by a process model that allows decision-makers to understand the how the behavior of critical hub infrastructures changes under shocks, and which process-related measures contribute to resilience, complementing capacity expansion.

The resilience framework is schematically shown as the triple resilience triangle in Fig. 1, which shows systems performance over time for a disaster that hits at T_0. The three triangles highlight the combining absorptive and adaptive capacity as well as the rapidity of adaptation. We assume here that overall system performance needs to be maximized, typical performance indicators for hub infrastructures could be output or throughput rates; for performance indicators that require minimization (such as time required or extra cost), the triangles are flipped upside down.

The first triangle (light grey) corresponds to the traditional resilience triangle, which is based on the time to achieve predisaster performance level P_0 given that the disaster led to a drop in performance to absorption level P_1, defined as the minimum post-disaster system performance. The absorptive capacity is at the root of the definition of resilience by Holling (1973), who defined resilience as the ability of a system to absorb disturbance or change. Later, Bruneau et al. (2003) defined absorption as the abrupt reduction of performance, a definition we follow here. The closer P_1 is to the original performance level P_0, the better the absorption capacity of the system, and the easier it is to reach predisaster performance.

The second and third triangle complement the traditional view to integrate the aspect of adaptation, which requires a performance level P_3 that goes beyond recovery to the initial state and exceeds the initial performance level P_0 to cope with the required expansion of services. Here, we refer to Rose (2007), who provided an indication of an upwards behavior to denote improvements in systems performance via adaptive behavior, and described the occurrence of a temporary equilibrium. These observations are the basis for our conceptualization. To clearly denote and analyze system behavior, we define the adaptation level as this new steady state of performance, or temporary equilibrium P_3 at time T_3 (dark triangle). Yet, this equilibrium is typically lower than the peak performance level P_2, defined as maximum performance that is reached in response to the disaster indicating an overshoot to compensate for the backlog caused by the increased load needed.

For the rapidity dimension, we go beyond the traditional definition that focus on recovery to the initial state and follow D'Lima and Medda (2015) who understand the rapidity dimension of resilience as the time of return to an equilibrium after a disturbance. Here, the new equilibrium is the adaptation level P_3. Therefore, the rapidity of adaptation is measured as the time after the disaster,

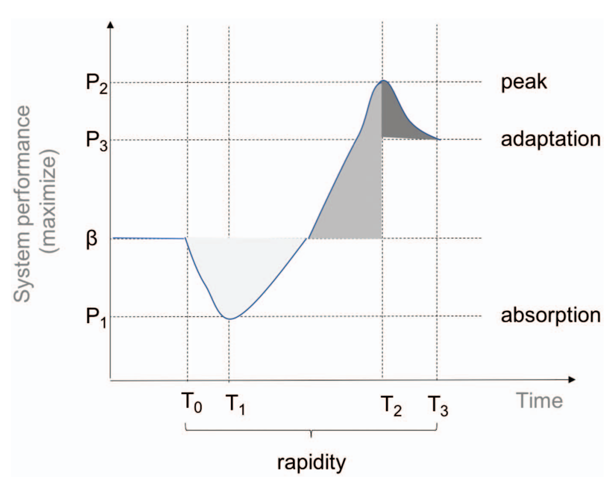

Fig. 1. (Color) Triple resilience triangle.

or disturbance to achieve adaptation ($T_3 - T_0$). In most traditional framework, such as Bruneau's original work, the disruption or disturbance is disturbed immediately (Bruneau et al. 2003), and in these cases, $T_0 = T_1$. Because we are here interested in the performance of a hub infrastructure that is subject to feedback loops and delays in other parts of the system, however, airport $T_0 < T_1$. The use of T_0 as a reference point also refers to the need to achieve specific performance levels in terms of time post disturbance. In humanitarian relief, for instance, it is instrumental to reach vulnerable populations within a specific time after the disaster to ensure they are supplied with vital relief items, such as water, food, or medical supplies.

In addition, it is possible that predisaster levels are not achieved. In this case, the adaptive level P_3 will be below P_0, and the peak level or overshoot P_2 is not achieved. Fig. 1 also highlights that the resilience and recovery functions are nonlinear. This triple-resilience-triangle approach allows policy-makers to gain insights into the performance of critical hub infrastructures, because it combines the analysis based on established resilience concepts with an analysis of the required adaptation and rapidity.

Measuring Airport Resilience: Process Model and Key Performance Indicators

To frame and scope the system, we first map out key actors and their influence on the operations of a disaster-affected airport based on a literature analysis including reports and guidelines from practice as shown in Fig. 2. We focus here on those key actors that make decisions about or carry out physical movements in the system (displayed in grey in Fig. 2).

In the case of airports, key processes such as scheduling, parking, and loading/unloading are impacted by a disaster and hence have an important effect on the airport operations (Veatch and Goentzel 2018). As such, what is needed is a systematic consideration of rapid adaptation at the process level reflecting the changed system properties. Process models have been used frequently to study airport systems (Manataki and Zografos 2010; De Neufville 2016). Particularly, discrete event models have been used successfully to study passenger streams (Verbraeck and Valentin 2002; Joustra and Van Dijk 2001) or air cargo operations (Nsakanda et al. 2004). Typically, such models are built for each airport individually although the underlying questions for each model and airport are similar. Therefore, we here follow Verbraeck and Valentin (2002) and Manataki and Zografos (2009) and propose a generic mesoscopic model that captures key features and can be easily adapted to a specific airport.

The effect of policies to improve resilience is measured via a set of key performance indicators (KPIs). The KPIs are measured for three key subsystems/components of the system, i.e, gate selection, aircraft unloading, and warehouse operations. By quantifying these indicators for every component, overall insights are gained into the resilience of the airport system. To test their robustness, the policies will be evaluated under different scenarios.

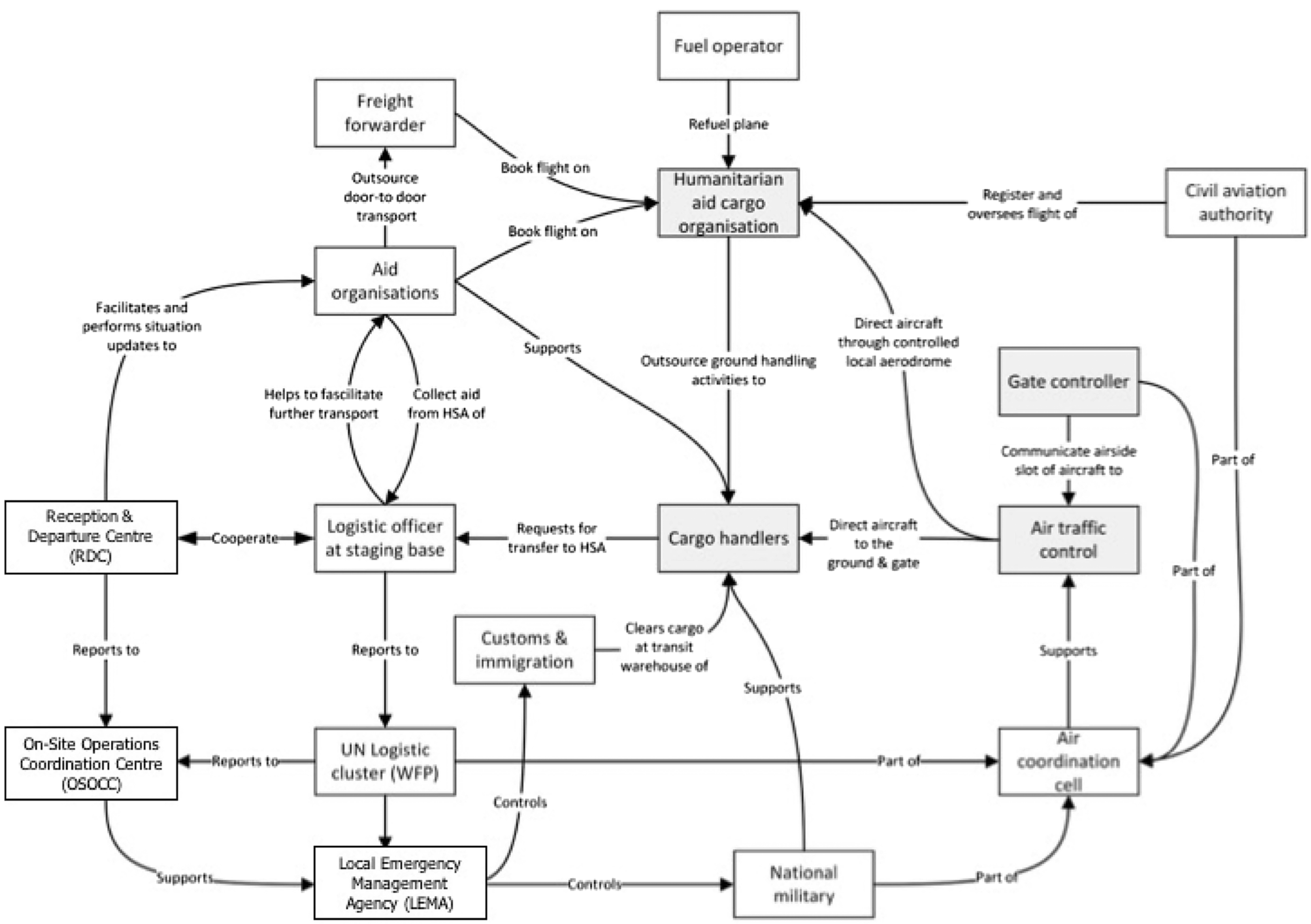

Fig. 2. Key actors at airports in disasters. Focus of this paper highlighted in grey.

Process Model

We develop a conceptual model of an airport to investigate the operations of the system and analyze generalized dynamics of the adaptation processes. We assume that the main shock to the airport consists in the rapid and massive influx of flights and goods, resulting in strained airport processes. While we assume there is no direct damage to the physical airport infrastructure such as runway or warehouse buildings, stresses stem from limited capacity in terms of human resources and equipment. Within the overall airport logistics system, Fig. 3 highlights that we focus on the following three critical system components:

1. Gate selection: assignment of incoming aircraft to docks and taxi time;
2. Aircraft unloading: loading of cargo from aircrafts and movement to transit warehouse taking into account aircraft type, cargo, available resources, and equipment;
3. Warehouse operations: handling, customs clearance, bulk breaking, and loading on trucks for transport to the affected region, typically via a Humanitarian Staging Area. Processes depend on cargo type, available resources, and equipment.

Key Performance Indicators

The resilience challenge for an airport impacted by a disaster is to adapt their logistics and cargo performance beyond the normal level of operations to cope with the increase of incoming flights and freight as part of the unfolding disaster response operations. We selected the following three throughput-related KPIs to measure the ability of the airport to rapidly adapt to these new requirements: (1) the total amount of cargo handled per hour; (2) the total amount of idle cargo, i.e., cargo that is still in the system (in tons); and (3) the average throughput time of one unit of cargo (in hours). These KPIs are motivated and characterized in more detail below. Importantly, we here focus on the resilience of the airport system as such to ensure its rapid adaptation to the surge of incoming flights, thereby focusing on the supply side. If a policy-maker rather focuses on the role of infrastructures for community resilience, metrics that take into account the demand-side such as suggested by Didier et al. (2018) need to be used.

The KPIs are presented individually and not combined into a single measure for three reasons: (1) different decision-makers may have different priorities, and displaying the results separately enables them to make choices and trade-offs based on their preferences; and (2) the KPIs are correlated, e.g., idle cargo and throughput, and therefore a (linear) aggregation to a single indicator is flawed as the necessary condition of independence is violated; and (3), showing how the KPIs evolve over time allows decision-makers to gain important insights into the timing of their policies and the resulting behavior of the airport system.

KPI 1: Cargo Processed (tons/hour): The cargo processed at the airport measures the number of tons of cargo that leaves the airport system (or system components) per hour, which is an indicator for the processing capacity of the airport. The inflow of cargo is beyond the control of the decision-makers at the airport (Veatch and Goentzel 2018). As such, it presents one of the external factors to which the airport system rapidly needs to adapt. Following Chen and Miller-Hooks (2012) and their work on express logistics, the total cargo processed or throughput is decisive for airport logistics under time pressure. The prototypical behavior of KPI_1 is shown in Fig. 1. After an initial drop in the response to the disaster to P_1, the performance increases to peak level P_2 and the reaches a new steady state P_3. The absorptive capacity of KPI_1 is measured by comparing the relative difference between P_0 and P_1. Adaptive capacity is measured by comparing the relative difference between P_3 and P_1.

KPI 2: Idle Cargo (tons): The amount of unused aid at airports is a well-document significant problem that leads to congestion at the airport (Holguín-Veras et al. 2012). The severity of the congestion is measured by the amount of cargo (in tons) that is not handled or idle. Idle cargo needs to be minimized because it affects the airport system, and too much idle cargo will disrupt the entire airport. For example, planes are unable to land if the runway is blocked by parked aircrafts.

As the idle cargo needs to be minimized, the expected typical behavior of this KPI is flipped upside down. In the initial state P_0, the airport is free of idle cargo. But with the surge of incoming flights and goods, the maximum idle cargo at the airport P_1 representing the absorption level. The shape of the curve of idle cargo is influenced by two main factors: (1) the inflow (cf. KPI 1), and (2) the outflow of cargo. The inflow will reflect the amount of incoming flights, and the cargo processed, while the outflow can be addressed by changed handling policies or creating additional storage capacity. Through an implementation of policies, or change of flight schedule, the idle cargo is reduced and reaches a new steady state. According to the work on material convergence at airport (Holguín-Veras et al. 2012; Veatch and Goentzel 2018), airport are unlikely during the response phase to clear all idle cargo, and $P_2 = P_3$. This implies that the airport does not reach predisaster performance levels P_0, and the time difference $T_2 - T_0$ represents the rapidity of adaptation.

KPI 3: Throughput Time (hours): The massive influx of aircraft and goods combined with reduced capacity of the airport will typically increase throughput times in the initial phase of the response. Here, we measure the average throughput time as an indication how long cargo remains in the airport system. Because the KPI needs to be minimized, the absorption level P_1 for KPI_3 is defined as the maximum average throughput time owing to the shock. The higher the absorptive capacity of the airport is, the smaller the difference between P_0 and P_1. The adaptation level $P_2 = P_3$ is defined as the new stable state after implementation of all adaptive measures at process level and the processing of any potential backlogs. The adaptive capacity of the airport with respect to KPI_3 is measured by the relative difference between P_2 and P_1. The rapidity of adaptation capacity is given by the time difference between T_2 and T_0.

For each KPI the following three variables have to be defined: a critical bottom level value for the absorptive capacity, a required service level value for the adaptive capacity, and the rapidity of adaptation. These levels define the values within which the airport needs to operate, or the safe operating space. If those values are exceeded, the airport system is said to collapse with detrimental consequences to both the operations at the airport as well as the humanitarian relief. Table 1 summarizes the critical threshold values for absorption, adaptation, and rapidity for the three KPIs and the three system components, according to the above discussion. For all KPIs the rapidity is measured by the time between T_4 and T_0. Here, we choose a threshold of 14 days as a typical recovery time, corresponding to experiences from the earthquakes in Nepal and Haiti (Stanhope 2010; Logistics Cluster 2015). After this initial chaotic period, the response will transition into a more stabilize and planned phase (Baharmand et al. 2019), in which ground transportation and sea ports become increasingly important, introducing another yet another regime and equilibrium for the airport.

The critical levels for absorption and adaptation are defined per KPI. For KPI_1 (cargo processed), the critical absorption level is set to 0, meaning that cargo must be processed. Based on past studies about airports in disasters (Neudert 2010; Veatch and Goentzel 2018), the critical level for the adaptive capacity that must be

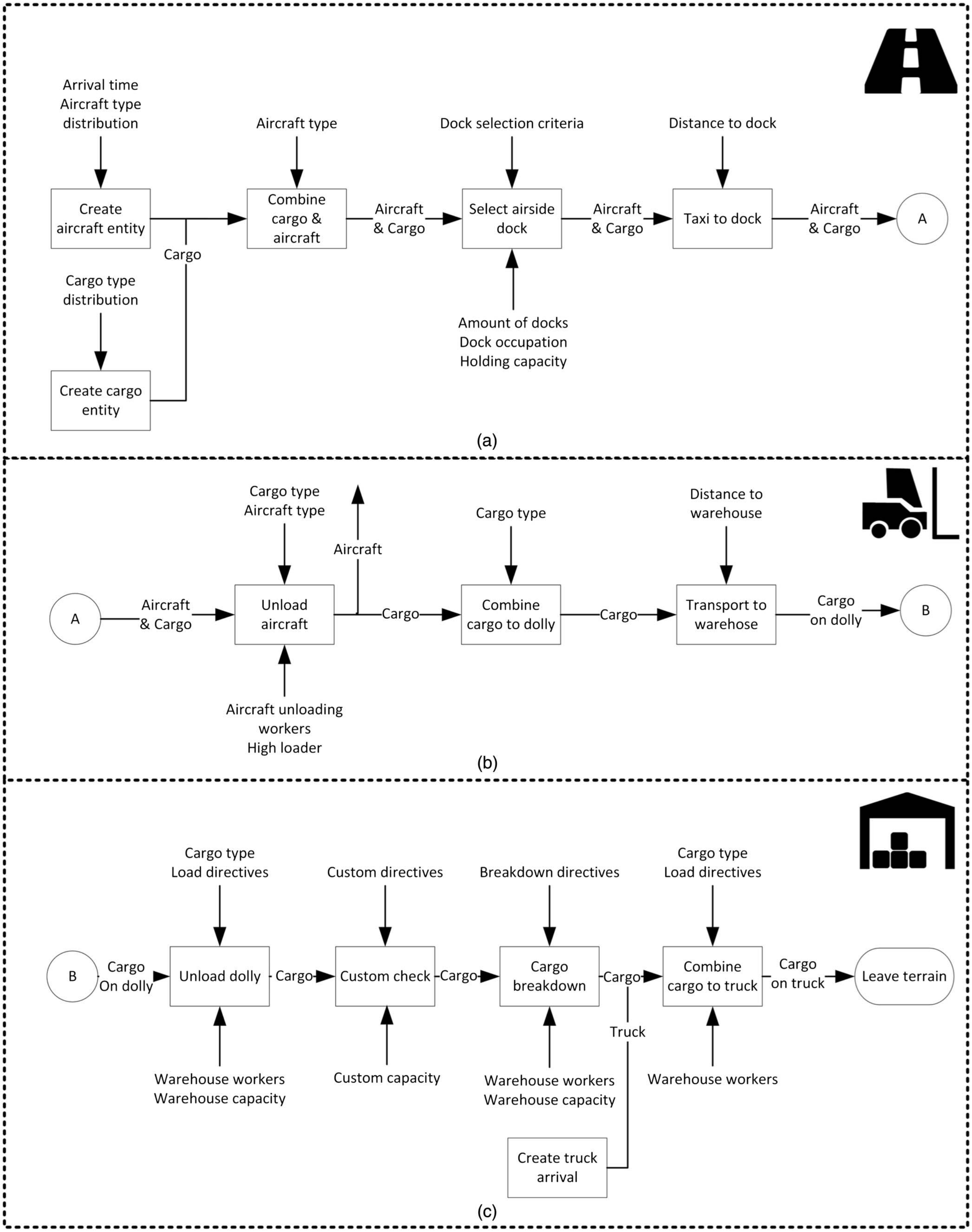

Fig. 3. Metamodel of the airport system simulation. Arrows from top to bottom represent control factors. Arrows from bottom to top represent resources needed. Horizontal arrows represent flows for the three system components: (a) dock and gate selection; (b) aircraft unloading; and (c) warehouse operations.

Table 1. Critical level of airport system per component and KPI for absorption (AB), adaptation (AD), and rapidity of adaptation (RA). If level are exceeded as indicated in the table, the airport system collapses

	KPI								
	Processed cargo			Idle cargo			Throughput time		
Component	AB (t/h)	AD (% of P_0)	RA (days)	AB (t)	AD (t)	RA (days)	AB (h)	AD (days)	RA (days)
Gate selection	<0	<400%	>14	>375	*	>14	>72	*	>14
Unloading	<0	<400%	>14	>0	*	>14	>72	*	>14
Warehouse ops	<0	<400%	>14	>375	*	>14	>72	*	>14

Note: (*) indicates that a new temporary equilibrium or steady state is reached.

reached is set to 400% of the level of normal operations P_0. For KPI_2 (idle cargo), we assume that the initial holding capacity at gate selection and warehouse operations is 375 t, while at unloading, no idle cargo is tolerated. Adaptation levels are defined as reaching a new temporary equilibrium. KPI_3 throughput time the critical absorption level P_1 for is set to be the maximum time that the cargo can be stored until it expires (e.g., because of cold chain issues) or is not needed any further in the humanitarian assistance (e.g., search and rescue equipment is only needed in the first 72 h). As for KPI_2, critical adaptation level is set to reaching a new temporary equilibrium.

Case Study: Airport Resilience Policies and Scenarios

We illustrate and test our framework via a stylized case study that functions as a proof of concept. The model and underlying data are based on a combination of empirical data from the Nepal earthquake of 2015 (Aydin et al. 2018; Baharmand et al. 2017) and the Haiti earthquake of 2010 (Veatch and Goentzel 2018). The data sets of these two disasters were gathered via expert interviews with professionals in airports in disasters (from US Airforce, DHL, and Dnata) and literature research. By applying the model and resilience framework to the case, insights are gained about how and why certain behavior appears.

Resilience Policies

While the resilience literature often focuses on how to define and assess infrastructure resilience or predict recovery and adaptation rates based on historical data (Barabadi and Ayele 2018), there are fewer studies that evaluate resilience policies. For recovery planning, there are some authors that suggest the exploration of recovery policies via probabilistic techniques (Bristow and Hay 2016), or reinforcement learning (Memarzadeh and Pozzi 2019). Other approaches define the recovery planning as a sequential decision problem, which is optimized in a dynamic programming approach (Nozhati et al. 2019; Faturechi et al. 2014). These approaches, however, use a highly stylized and simplified representation of the airport system that does not represent the underlying process dynamics. More specifically for transportation and logistics, resilience, and recovery planning models largely focus on complex (infrastructure or relational) networks and analyze the impact of a policy on its topology and composition (Aydin et al. 2018; Miller-Hooks et al. 2012; Turnquist and Vugrin 2013). Other approaches include the option to reduce failure probabilities (Lou and Zhang 2011; Sherali et al. 2011). All these approaches have in common that they focus on network or systems design and capacity. As such, they are instrumental in recognizing the criticality of a (network) node, but they are less suitable to develop resilience policies at process level, especially considering the required adaptivity going beyond predisaster performance levels that we address here.

Based on the literature and expert interviews, we propose six policies that are designed to capture structural and process related measures to rapidly adapt the airport system, ranging from extra resources to scheduling and capacity building cf. Table 2.

These policies vary with respect to their lead time (i.e., the time it takes from implementation to impact) and cost. While prioritization and provision of extra holding capacity on grass are process-related policies that can be implemented with immediate effect and without cost, installing temporary warehouses or increasing the resources available will take more time and cost. For Nepal, the cost of running an extra warehouse has been estimated at $850 per day, while increasing the workforce (including equipment) is estimated at $700 per day (Baharmand et al. 2019). However, the prizing will largely vary with the case study area, and the choices made for storage capacity (e.g., tents, containers) (Şahin et al. 2014).

Table 2. Six policies to improve the resilience of airports

Policy	Effect
1. Bring in extra resources	Extra unloading equipment and specialized workers to increase the handling capacity of the airport (Logistics Cluster 2010). This policy is divided into three subpolicies with varying arrival times (3, 4, or 5 days postdisaster).
2. Prioritize on size	Prioritization mechanism on aircraft size. Wide-body aircrafts need less time on the ground per cargo unit compared to smaller aircrafts (Veatch and Goentzel 2018).
3. Prioritize on cargo type	Aircrafts packed with buildup pallets (BUP) are prioritized over aircraft packed with loose boxes, because they require less unloading time (Veatch and Goentzel 2018).
4. Provide temporary warehouses	Increasing the warehouse capacity creates extra buffer capacity (Logistics Cluster 2015), thereby raising the maximum absorption level of idle cargo in the warehouse component to 1875 t.
5. Increase the holding area	Increasing the holding area by parking small aircrafts on grass and using all available pavement on the airport (Hanaika et al. 2013). This results in an increased absorption level of the idle cargo KPI in the gate selection component to 750 t.
6. Combined policy	Consisting of all previous policies (split into subpolicies according to arrival of resources). Maximum absorption level of the idle cargo at gate selection is 750 t and at warehouse operation component 1875 t.

Model Variables and Parameters

To test the impact of the policies on the gate selection, unloading aircraft and warehouse operations, we define key variables that may influence the outcomes for these policies. For each of the three airport processes we define the stochastic variables as listed in Table 3.

All variables have a specific distribution and values selected from literature, as referenced in the table. For the gate selection, we introduce two variables: the type of aircraft arriving, resp. small, narrow, and wide aircraft types with a probability of resp. 41%, 52%, and 7%, and arrivals for a peak day of 60, 80, or 100 incoming flights that day with a discrete uniform distribution, i.e., the outcomes are equally likely to happen. For the unloading aircraft process, we define two variables with a normal distribution for each of the three aircraft types of small, narrow, and wide: the unloading time for buildup pallets (BUP) and for bulk packed cargo. Finally, for warehouse operations, we introduce the breakdown cargo variable with a continuous uniform distribution ranging from 10 to 30 (min). All further airport model parameters and their underlying rationale and references are provided in Table 4.

The model can now be executed for any random selection of the variables' values above. The output of a run of the model delivers hourly values for the performance for the key system components (gate selection, unloading, and warehouse) under each policy in terms of the absorptive and adaptive capacity, and the rapidity of adaptation for the three KPIs (processed cargo, idle cargo, and throughput time). In addition, the overall performance for the airport system is assessed (processed cargo that is leaving the airport system; sum of idle cargo in all processes; average throughput time from arrival until cargo leaves the system).

As we focus on the immediate response phase with a duration of maximum 2 weeks (Logistics Cluster 2015), the run length of the model is set to 20 days, divided into two segments: a shorter segment corresponding to the pre-disaster situation and a longer segment covering the postdisaster situation. The second segment starts at 6 o'clock in the morning of the sixth day, enabling us to capture the full 14 days of the response phase.

Scenarios

Two elements have been identified that critically influence the swift recovery of an airport: the share of personnel able to work after a disaster, and the percentage of cargo that consists of loose boxes. In the ideal scenario, everyone is able to work, and there are no loose boxes in the cargo of the incoming planes. In contrast, a worst-case scenario is that 30% of the people stay away from work, and 30% of the cargo consists of loose boxes. The choice of 30% is arbitrary, but roughly corresponds to documented experiences in previous disasters and is large enough a value to contrast with the ideal scenario case.

To understand the impact of these situations on airport resilience, we set up a 2×2 experiment, with the four experimental conditions being the ideal scenario (0%,0%), the worst-case scenario (30%, 30%), and two intermediate conditions of (0%, 30%) and (30%, 0%) respectively. Within each condition we run the model 160 times, resulting in 95% of all model output values falling within an acceptable range of 10% around the mean output.

Table 3. Stochastic model variables

Variable	Variable distribution	Source
	Gate selection	
Aircraft arrival: small, narrow, wide	$\sim 41\%, 52\%, 7\%$	Kallen (2015)
Arrivals peak days	$\sim \mathcal{U}\, 60,80,100$	Neudert (2010)
	Unloading	
Unloading time BUP		Veatch and Goentzel (2018)
Small	$\sim \mathcal{N}(63, 55)$ (min)	
narrow	$\sim \mathcal{N}(119,66)$ (min)	
Wide	$\sim \mathcal{N}(183,80)$ (min)	
Unloading time bulk packed		Ballestero (2017)
Small	$\sim \mathcal{N}(158,138)$ (min)	
Narrow	$\sim \mathcal{N}(298,165)$ (min)	
Wide	$\sim \mathcal{N}(458,345)$ (min)	
	Warehouse operations	
Breakdown cargo	$\sim \mathcal{U}(10, 30)$ (min)	Interview DHL

Results

In this section, we present selected results of the model runs in the four different scenarios. A full results overview is available on a public repository (Feil 2018a). In the figures below, the outputs are Fcolor-coded as follows: blue shows the results in the (30%, 30%) scenario, red the results for the (0%, 0%) scenario, and green and yellow for the (30%, 0%) and (0%, 30%) scenarios, respectively. The purple line is a smoothed representation for the blue output. Figures show the results for the three KPIs of cargo processed

Table 4. Model parameters

Variable	Value	Source
	Gate selection	
Aircraft capacity: small, narrow, wide	(2, 8, 14 cargo units)	Kallen (2015)
Weight cargo unit	2.5 (t)	Kallen (2015)
Taxi lane	2 (km)	Google maps
Taxi speed	30 (km/h)	Jordan et al. (2010)
Baseline arrivals per day	18 (aircraft)	Cochran (2016)
Number of gates	10 (gates)	Veatch and Goentzel (2018)
Taxi lane capacity	150 (cargo units)	Cochran (2016)
	Aircraft unloading	
Dolly speed	15 (km/h)	Schoenmaker (2016)
Workers unloading	8 (workers)	Ballestero (2017), Interviews
Equipment unloading	1 (high loader)	Ballestero (2017), Interviews
	Warehouse operations	
Unloading dolly BUP	3 (min)	Schuppener (2016)
Unloading dolly bulk	7 (min)	Ballestero (2017); Kallen (2015)
Workers dolly	2 (workers)	Interviews
Workers breakdown	3 (workers)	Interview DHL
Customs scan	10 (%)	Schuppener (2016)
Customs scan duration	10 (min)	Schuppener (2016)
Customs capacity	1 (cargo unit)	Assumption
Loading time truck BUP	3 (min/unit)	Schuppener (2016)
Loading time truck bulk	7 (min/unit)	Schuppener (2016)
Truck capacity	4 (units)	Schuppener (2016)
Workers truck loading	2 (workers)	Schuppener (2016)
	General baseline	
Number of workers	24 (workers)	Interviews
Number of high loaders	3 (high loaders)	Interviews

(KPI_1), idle cargo (KPI_2), and throughput time (KPI_3). All figures show the behavior over time for each KPI before and after the disaster occurring at day 6. The graphs present hourly values. The fluctuations correspond to the day and night rhythm, which is primarily owing to the changing patterns of flights, with different day and night schedules. This leads to a peak in the processed cargo late in each day, which is then visible with some delay (owing to the lead times related to processing) in the idle cargo and throughput times.

Results for "No Policy" Option on the Airport System

We start of by looking at the results for the overall airport system for the no policy option, i.e., none of the six proposed policies are implemented. This option serves as a benchmark for our discussion on the resilience policies discussed below, and allows us to clearly understand the impact in the different scenarios.

As the modeling results in Fig. 4 show, this option highlights the importance of the loss in workforce, particularly for the processed cargo KPI: the scenarios with 30% loss of workforce (blue and green) perform significantly worse than the scenarios with full work force (yellow and red); irrespective of the amount of loose boxes. Given the lack of resources, the processed cargo drops from a base level of 10.6 t/h to 5.8 t for blue and green scenarios [see Fig. 4(a)]. With a full workforce available, the airport manages to slightly adapt and process some of the cargo that is coming in additionally as of day 6, yet remain far below the required adaptive level of at least 400% of P_0, or at least 42, 4 t/h after 14 days. Note that because we assume that there is no destruction of the airport, there is the downwards shock stems from a lack in workforce, which is not present in the yellow and red scenarios. In all scenarios, despite the reduced amount of incoming cargo, the idle cargo continues to increase over time, which also results in a continuously increasing throughput time [Fig. 4(c)]. As such, for all scenarios, the airport system quickly collapses, and adaptation levels or a new steady state are not reached.

Results for Extra Resources Policy on the Airport System

Given the impact of reduced personnel as observed in case nothing is done, we take a closer look at the effect of bringing in extra resources. In particular, we analyze the impact of extra resources arriving at the airport three, respectively five, days postdisaster (day 9, resp. day 11 on our time line), as shown in Fig. 5 and Table 5.

Most notably, Fig. 5, left hand side shows that adaptation is achieved for all indicators if extra resources arrive fast (three days postdisaster). However, if the additional resources only arrive with 2 days further delay, a massive amount of idle cargo and dramatically increased throughput times results [cf. Fig. 5, right hand side]. The higher fluctuations for the red and green scenarios as compared to yellow and blue stem from the fact that there are no loose boxes in these scenarios, which makes the day/night fluctuations of the work force in terms of processed cargo and throughput time more pronounced.

For further analysis we focus on the most extreme (blue) scenario, because all other scenarios show similar, albeit less pronounced, behavioral patterns (cf. Fig. 5). The results in Table 5 show that if extra resources are available three days postdisaster, a new equilibrium is reached for processed cargo after 3.5 days, for idle cargo after 8 days, and for throughput time after 12 days. If, however, extra resources are available only two days later, the airport system is unable to cope. While the absorption levels P_1 for processed cargo are the same for both cases and a peak level P_2 of 570% of P_0 is achieved (as compared to 540% for extra resources on day 3), the delay of achieving peak performance in cargo

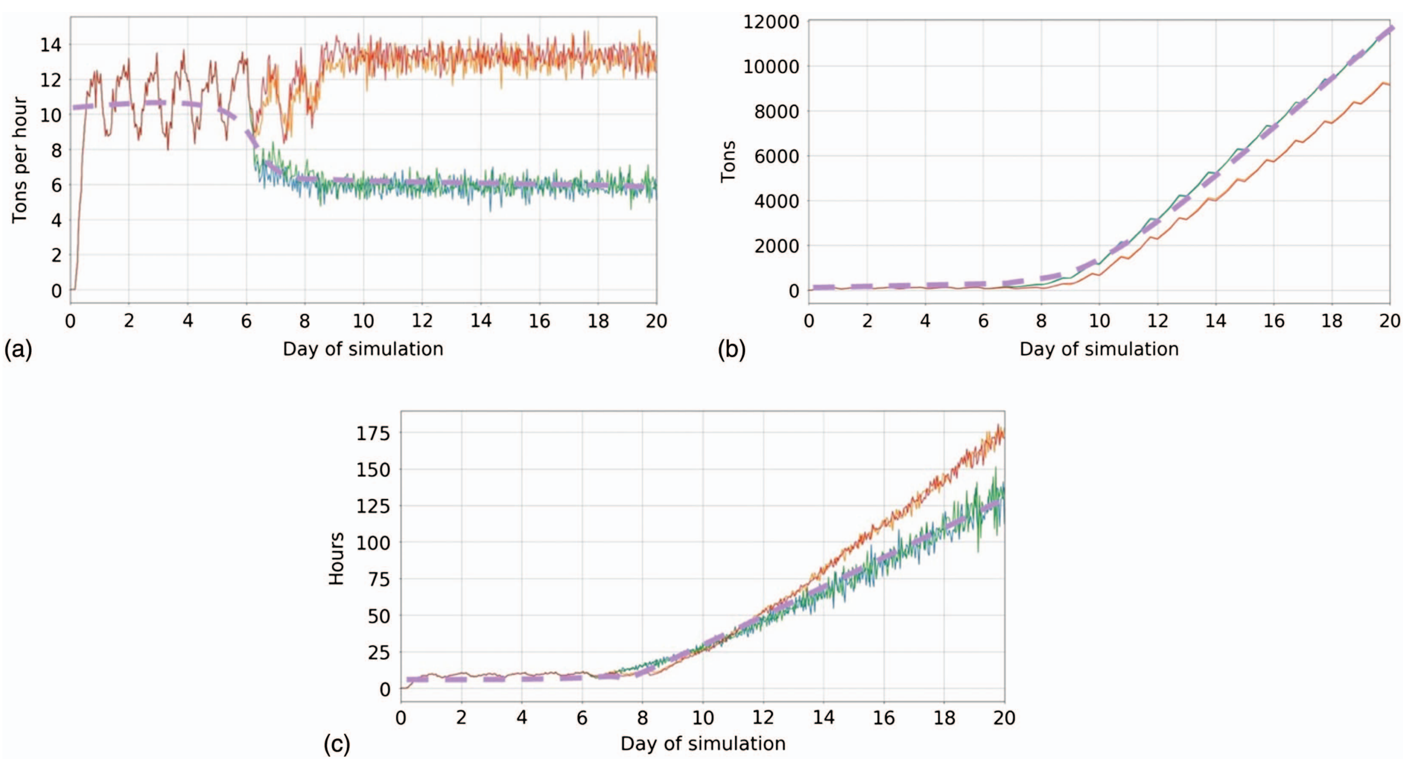

Fig. 4. (Color) Model results for no policy at airport system level. The plot shows the mean of all runs for the blue (30, 30), green (30, 0), yellow (0, 30), and red (0,0) scenario with (% loss workforce, % loose boxes). Purple line: smooth representation of the blue scenario: (a) processed cargo; (b) idle cargo; and (c) throughput.

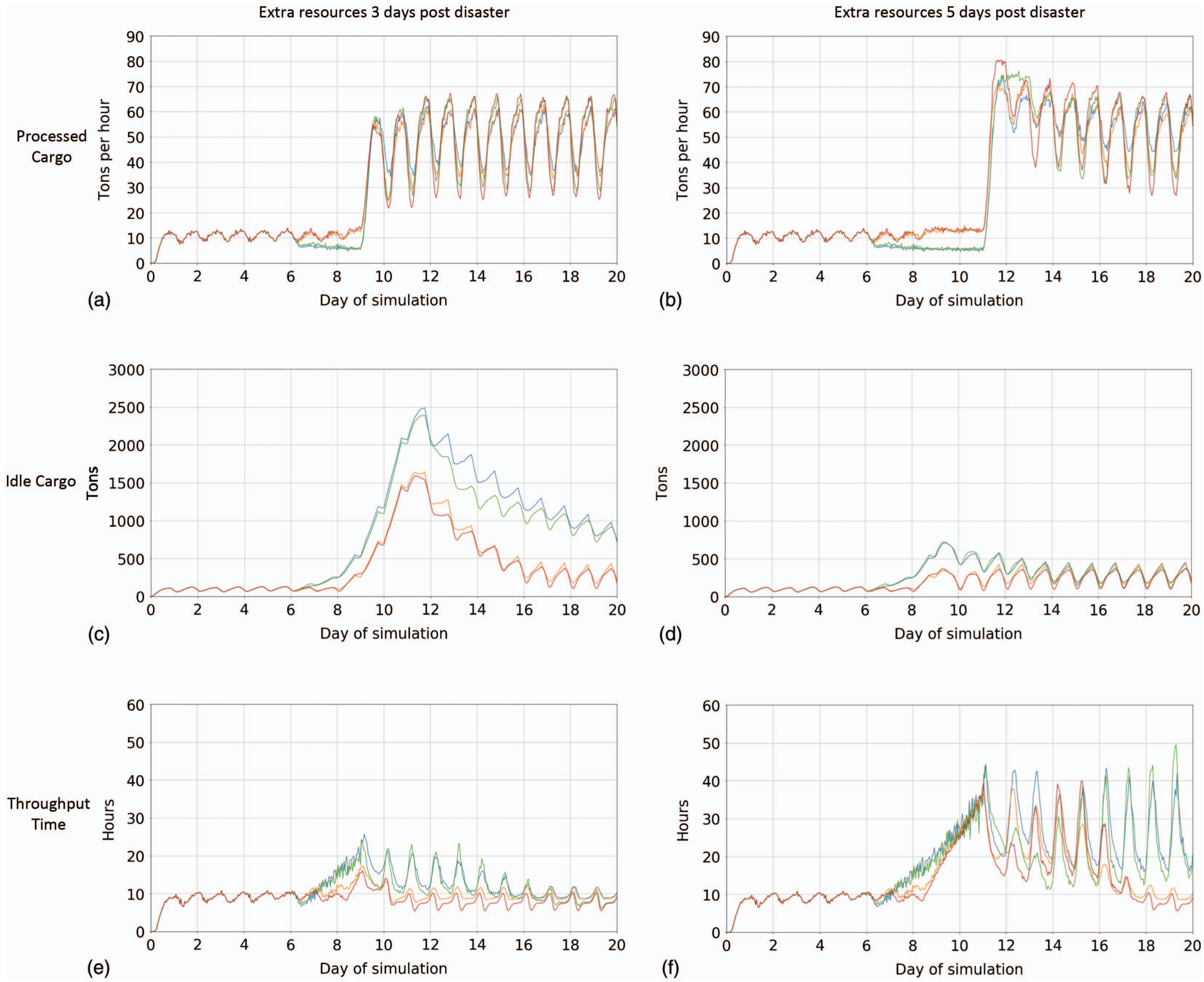

Fig. 5. (Color) Comparison of results for extra resources arriving 3 versus 5 days postdisaster at airport system level for all three KPIs. Scenarios: blue (30, 30), green (30, 0), yellow (0, 30), and red (0,0) scenario with (% loss workforce, % loose boxes): (a) extra resources 3 days postdisaster: processed cargo; (b) extra resources 5 days postdisaster: processed cargo; (c) extra resources 3 days postdisaster: idle cargo; (d) extra resources 5 days postdisaster: idle cargo; (e) extra resources 3 days postdisaster: throughput time; and (f) extra resources 5 days postdisaster: throughput time.

Table 5. Key values for the triple resilience triangle for the blue scenario for extra resources (ER) on day 3 and day 5 postdisaster

	Processed by system		Idle cargo		Throughput time	
Resilience indicator	ER day 3	ER day 5	ER day 3	ER day 5	ER day 3	ER day 5
T_1	2.6 days	4.4 days	3.5 days	5.8 days	3.2 days	5.3 days
T_2	3.1 days	5.1 days	n.a.	n.a.	n.a.	n.a.
T_3	3.8 days	6 days	n.a.	n.a.	n.a.	n.a.
T_4	8 days	n.a.	8 days	12 days	n.a.	n.a.
Rapidity	3.5 days	n.a.	8 days	n.a.	12 days	n.a.
P_0	10.6 t/h	10.6 t/h	88t	88t	8.2 h	8.2 h
P_1	5.8 t/h	5.8 t/h	755.4 t	1621.7 t	26.6 h	54.6 h
P_2	56.9 t/h	60.5 t/h	n.a.	n.a.	n.a.	n.a.
P_3	49.2 t/h	n.a.	325.7 t	n.a.	10.0 h	n.a.

Note: T_1 = reaching absorption level P_1 (worst systems performance); T_2 = recovery to base level P_0 (bounce back); T_3 = peak performance P_2 (bounce up); T_4 = achieving adaptation P_3; n.a. = not achieved; and ER = extra resources.

processing (6 days versus 3.8 days) for the extra resources arriving on day 5 roughly doubles P_1 for both idle cargo and throughput time as compared to extra resources arriving on day 3. This leads to an overcrowded airport, a delayed delivery of goods to the people in need, and eventually a collapse of the airport system.

Results of Policies on the Gate Selection Process

As an illustration of the results of the policies on airport processes, we focus in this section on the gate selection process. The policies illustrated are detailed next.

Prioritization by Cargo and Aircraft Size Policies

Fig. 6(e) shows that for the prioritization by cargo, the amount of workers available is decisive: the red and yellow scenarios (without loss in workforce) achieve a processing rate of about 37 t/h at gate, whereas the blue and green scenarios converge to 17.3 t/h. Contrarily, if prioritization is done by aircraft size, the scenarios fall into three categories, see Fig. 6(f). The red scenario performs best with an average processing rate of more than 30 t/h, the yellow and green scenarios (both characterized by 30% loose boxes) achieve 22 t/h, while with 15.1 t/h the blue scenario performs worse than for the prioritization by cargo, which is still about 23% better than the do nothing option at gate level.

However, the performance for both prioritization policies is far below the required 400% beyond P_0 in increase and not sufficient to deal with the incoming amount of cargo. As such, it leads to a collapse of the airport system due to a continuously increasing amount of idle cargo and throughput time (see Fig. 6). The distinction between red and yellow versus blue and green for prioritization by cargo (Fig. 6, left hand side) and red versus green and yellow versus blue (Fig. 6, right hand side) is also reflected in the idle cargo, which results in the similar categories for both prioritization policies. In both cases the amount of cargo that is idle at the taxi lane is over 8,000 t at the end of the 20th day for the blue scenario,

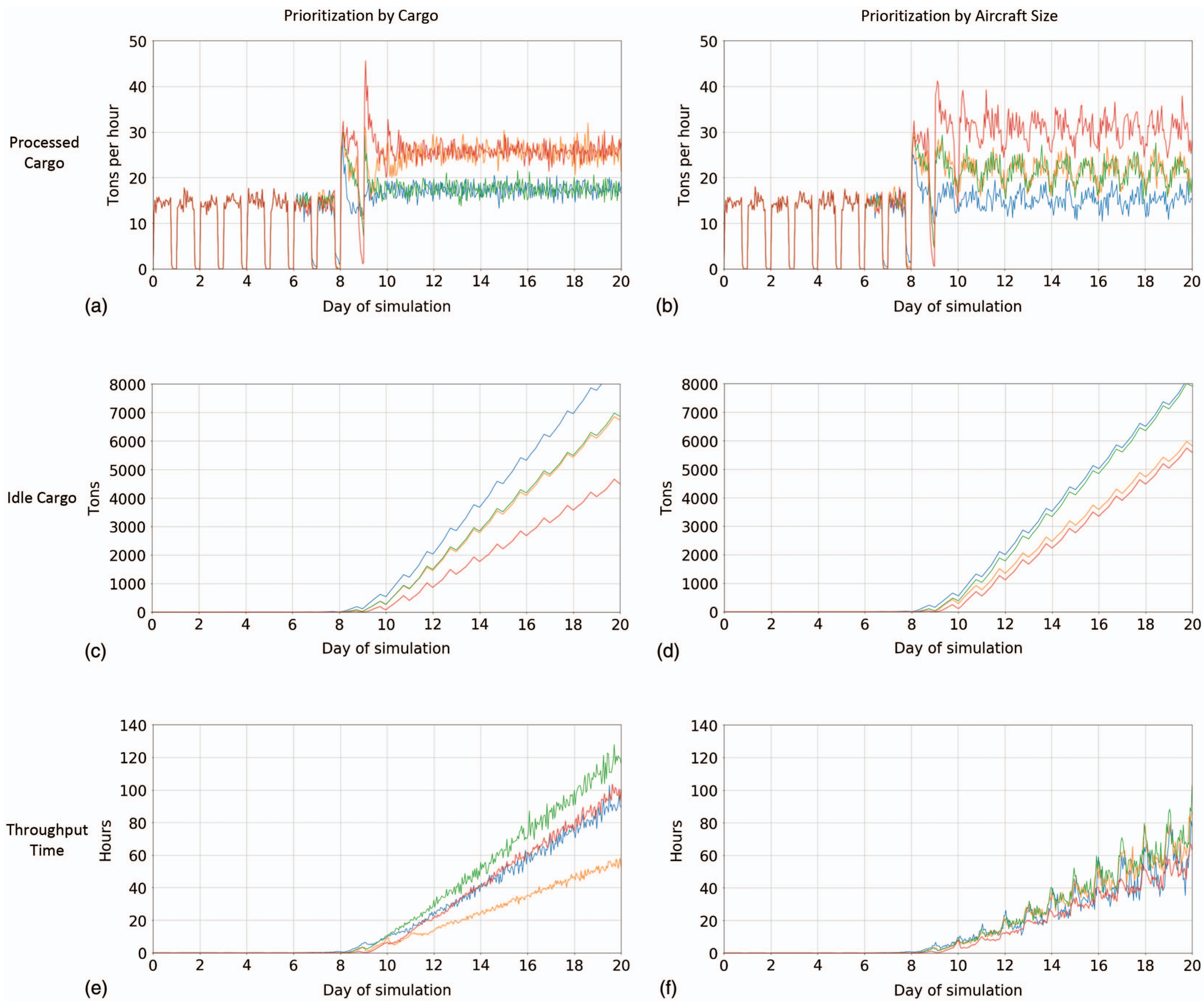

Fig. 6. (Color) Comparison of results for prioritization policies at gate component system level for all three KPIs. Scenarios: blue (30, 30), green (30, 0), yellow (0, 30), and red (0,0) scenario with (% loss workforce, % loose boxes): (a) prioritization by cargo: processed cargo; (b) prioritization by aircraft size: processed cargo; (c) prioritization by cargo: idle cargo; (d) prioritization by aircraft size: idle cargo; (e) prioritization by cargo: throughput time; and (f) prioritization by aircraft size: throughput time.

and in all cases by far exceeds the holding capacity of 375 t. As the prioritization according to cargo (Fig. 6, left hand side) implies that the aircrafts packed with loose boxes are not prioritized, the average throughput time increases for the red and green scenarios over the yellow and blue, showing the impact of the policy and leading to an average throughput time of under 60 h by day 20 for the yellow scenarios, as compared to more than 120 h for the green scenario. For the prioritization by aircraft size (Fig. 6, right hand side), the scenarios perform more similar, with the yellow and green scenarios (including loose boxes) showing a slightly worse performance.

Combined Policy: Extra Resources with Prioritization and Extra Holding Area

In Fig. 7, the analysis of a combination of extra resources with prioritization by aircraft size and an increase of the holding area is displayed for the gate selection component and the critical KPI Idle Cargo. Combining the policies has a positive effect resulting in 30% less idle cargo compared to the extra resources policy only. By adding extra holding capacity, the initial holding capacity is doubled from 375 to 750 t with immediate effect. The initial amount is only sufficient if the extra resources arrive on 3 days postdisaster, because the absorption level is just over 200 t. In this case, the airport system reaches its adaptation level of 50.6 t of cargo 1 day later, i.e., 4 days after the disaster hit. If extra resources arrive later, the airport depends on the extra holding capacity. Doubling capacity is sufficient if the extra resources arrive 4 days postdisaster because the absorption level is about 620 t [cf. Fig. 7b]. In this case, the adaptation level of 50.9 t is reached 10 days after the disaster, almost a week later than for extra resources arriving on day 3. If the resources arrive 5 days postdisaster or later, the airport is unable to handle the incoming aircrafts even with double capacity. In this case, the absorption level raises to 1372.3 t, adaptation levels are not reached, and the airport should decline landing requests.

Results of All Policies on the Airport Processes in the Worst-Case Scenario

We here present the results of the analyzed policies at airport process level for the worst-case (blue) scenario. We chose this scenario as it represents a likely disaster setting characterized by reduced capacity and a significant share of loose boxes. Table 6 shows the performance of policies with respect to all KPIs and components for this scenario. Several important findings can be noted.

First, while bringing in extra resources improves airport performance for all KPIs and components, the impact of targeted policies can have a negative or rippling effect as the increase in processing of incoming flights cannot be adequately dealt with. For instance, we see that the prioritization on aircraft size and cargo type improves adaptation (and cargo type also rapidity) for processed cargo at unloading (15 and 17.3 versus 11.8), yet these policies have a negative impact on idle cargo and throughput time as compared to the no policy scenario for the unloading component (7.5/4.5 versus 3.7 and 8.1/8.0 versus 7.2) because there is no capacity to store and handle the additionally incoming goods. This finding highlights the need for an integral approach to modeling the airport system.

Second, the results in the policy effect Table 6 show that the gate selection and the warehouse operations processes are more prone to failures that eventually cause the airport to collapse than the unloading process. This suggests that these two processes are the most critical in enabling resilience of the airport.

Third, we see that capacity extending policies such as adding holding areas or temporary warehouses are only useful if there are sufficient resources to exploit their potential. Similarly, while

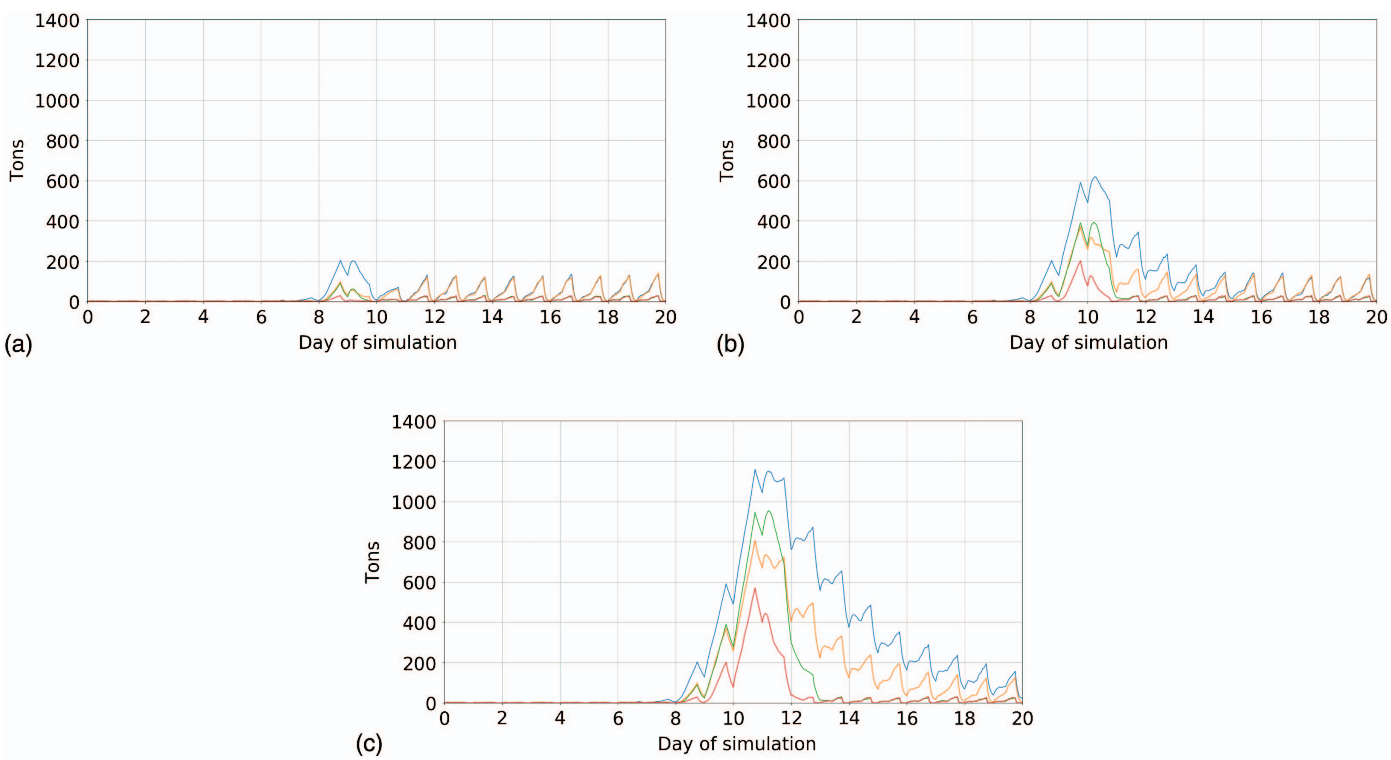

Fig. 7. (Color) Performance of idle cargo KPI for combined policy (extra resource and double prioritization). Scenarios: blue (30, 30), green (30, 0), yellow (0, 30), and red (0,0) scenario with (% loss workforce, % loose boxes): (a) extra resources 3 days postdisaster; (b) extra resources 4 days postdisaster; and (c) extra resources 5 days postdisaster.

Table 6. Triple resilience analysis of absorption level (AB), adaptive level (AD), and rapidity of adaptation (RA) based on the blue scenario. Units: RA (days); and AB and AD for processed cargo (t/h), for idle cargo (t), for throughput time (h). Bold cells indicate that absorption levels exceed capacity of holding areas or warehouses for AB or that convergence to AD is not reached within 14 days (RA). Note that capacity for holding areas and temporary warehouses are increased for the combined policies, leading to higher failure thresholds

Policy	Processed cargo			Idle cargo			Throughput time		
	AB	AD	RA	AB	AD	RA	AB	AD	RA
Gate selection									
No policy	11.0	12.0	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**
Extra resources on the 3rd day	11.0	61.3	4	276	80	4	9.4	1.3	4
Extra resources on the 4th day	11.0	61.3	10	**930**	77	10	22.1	1.4	10
Extra resources on the 5th day	11.0	61.3	**fail**	1831	**fail**	**fail**	38.4	4.7	13
Prioritization on aircraft size	11.0	15.1	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**
Prioritization on cargo type	11.0	17.3	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**
Extra holding area	11.0	12.0	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**
Temporary warehouse	11.0	12.0	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**
Combined policy 3rd day	11.0	69.3	4	203	51	4	6.1	1.3	4
Combined policy 4th day	11.0	76.3	10	619	51	10	12.9	1.3	10
Combined policy 5th day	11.0	79.2	**fail**	**1372**	51	**fail**	21.4	4.27	12
Unloading									
No policy	11.0	11.8	6	3.7	3.7	6	7.2	7.2	6
Extra resources on the 3rd day	11.0	61.3	4	4.5	2.1	4	7.2	2.7	4
Extra resources on the 4th day	11.0	61.3	10	5.6	2.2	10	8.3	2.9	5
Extra resources on the 5th day	11.0	61.3	11	5.6	2.9	11	8.4	3.6	6
Prioritization on aircraft size	11.0	15.0	6	7.5	7.5	6	8.1	8.1	6
Prioritization on cargo type	11.0	17.3	4	4.5	4.6	4	8.0	8.0	4
Extra holding area	11.0	11.8	2	3.7	3.7	6	7.2	7.2	6
Temporary warehouse	11.0	11.8	2	3.7	3.7	6	7.2	7.2	6
Combined policy 3rd day	11.0	70.7	4	5.9	2.3	4	8.0	2.8	4
Combined policy 4th day	11.0	75.8	6	7.0	2.5	6	8.3	2.8	5
Combined policy 5th day	11.0	86.5	8	7.9	2.6	8	8.3	3.0	6
Warehouse operations									
No policy	5.8	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**
Extra resources on the 3rd day	5.8	56.9	8	**523**	242	8	6.1	0.6	4
Extra resources on the 4th day	5.8	60.3	**fail**	**693**	**fail**	**fail**	10.7	1.0	8
Extra resources on the 5th day	5.8	60.5	**fail**	**836**	**fail**	**fail**	13.8	1.6	13
Prioritization on aircraft size	5.8	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**
Prioritization on cargo type	5.8	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**
Extra holding area	5.8	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**
Temporary warehouse	5.8	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**	**fail**
Combined policy 3rd day	5.8	62.2	12	580	247	12	5.6	0.6	4
Combined policy 4th day	5.8	68.1	**fail**	949	**fail**	**fail**	9.0	1.2	8
Combined policy 5th day	5.8	74.1	**fail**	1160	**fail**	**fail**	10.3	2.1	12

prioritization policies are able to increase the performance for processing cargo at gate selection and for unloading by 26% to 44%, this is not sufficient to prevent the collapse of the system. Rather, the increase of processed cargo results in more idle cargo. Taken alone, these policies do not perform significantly better than the no policy option. However, in combination with extra resources, they are able to create buffer capacity for the airport and lower the dependence on the swift arrival of resources in terms of absorptive capacity and increase efficiency. These findings lead to an important conclusion: while there is a well-documented urge among decision-makers to rush to action after a disaster by implementing policies that have immediate results, no lead time and no associated cost (such as prioritization or capacity increase at the airport), the policy with the longer lead time of increasing extra resources in terms of staff and equipment has, in fact, the greater contribution to airport resilience.

Timeline Visualization for the Implementation of Policies

To help decision-makers understand the timing of critical decisions under different scenarios, we create a timeline visualization such as the one shown in Fig. 8. The figure provides information for decision-makers on the timing and related consequences for the combined policy, which is the best performing policy in the blue scenario (Table 6). The different critical times are denoted as A, B, C etc., indexed for the various scenarios. Corresponding to the preceding discussion, the visualization shows that in the blue scenario the airport logistics system can only absorb and recover if the extra resources arrive within the first three days after the disaster. If extra resources arrive later, the system can absorb the influx of aircraft, but not reach a stable level within 2 weeks. If the extra resources arrive more than 5 days after the disaster, the airport cannot absorb the amount of cargo and collapses.

Fig. 8 also shows that for three scenarios (blue, green, yellow), the airport reaches the limits of its coping capacity at day 11, five days after the disasters strikes, unless extra resources arrive on time. In both scenarios with limited human resources (blue and green), if extra resources arrive late, the airport does not reach a new steady state within 2 weeks after the disaster, with serious implications for the response. The yellow scenario highlights the implications of loose boxes: because they are an additional strain on airport capacity and workforce, the yellow scenario also can lead to the collapse

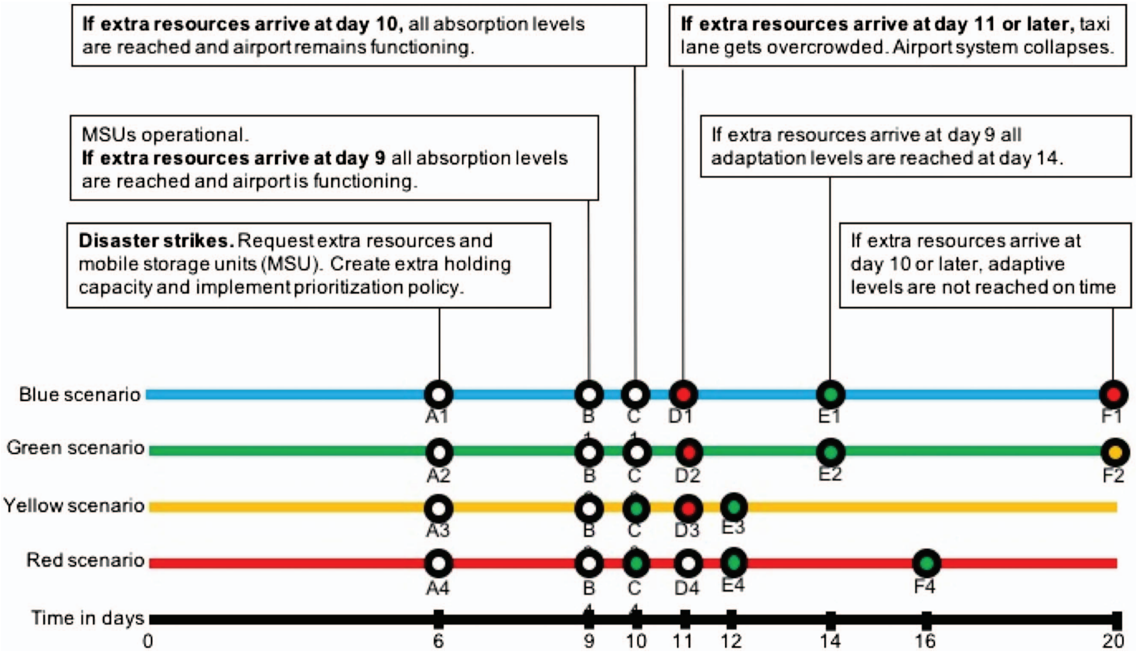

Fig. 8. (Color) Timeline for implementation of combined policy and critical points for the airport system's resilience. Details for the blue scenario.

of the airport, unless additional resources arrive. Only for the red scenario (with full workforce available and no loose boxes), the airport reaches adaptation levels at the latest on day 16 irrespective of when the extra resources arrive.

Validity of the Model and Results

During the process of model building, a main concern for the modeler is how closely the model reflects the real system it aims to represent. We have taken the following steps in validating our model and verifying its results: (1) historic output validation to validate the model conclusions, (2) face validation to validate the model assumptions, (3) internal validity test to validate the model output consistency, and (4) sensitivity analysis to validate the relationship between the input values and the model output values (Sargent 2007).

1. Historic output validation: Although the case used in this paper is stylized, the general findings should be in line with reality. We therefore compare the conclusions of the model output to historical events at the airports involved in the response of the Haiti in (2010) and Nepal in (2015) earthquakes (Veatch and Goentzel 2018; Aydin et al. 2018; Baharmand et al. 2017). First, our findings are in line with the literature on material convergence, which highlights that airports in disasters are frequently collapsing and vital goods cannot be processed on time (Holguín-Veras et al. 2012). Holguín-Veras et al. (2014) describe that about a third of the staff during the Tohoku Earthquake response was occupied sorting the incoming goods, and that 40-50% of warehousing was used for low priority items. While our model does not include the types of goods arriving, we can clearly confirm the need for extra resources to deal with the incoming goods, and the need for extra warehousing and storage space. Accordingly, the extra warehouse policy was also introduced in addition to extra resources during the Nepal response (Logistics Cluster 2015). If, indeed, the low or no priority item constitue 60% of the incoming goods (Holguín-Veras et al. 2007) reducing the amount of unwanted and unsolicited donations will drastically unburden the airport system. Moreover, we can confirm that the prioritization by aircraft size that was also used during the Haiti Earthquake response (Logistics Cluster 2010) does have a slightly positive impact on the performance. Thereby, we can confirm early research on congested airports (not in a disaster context), which found that overall delays and queuing times could be reduced (Janic 2009). As such, we can conclude that the suggested policies resulting from the model are in line with real-world policy implementations.
2. Face validation: In order to validate the underlying assumptions of the model, we conducted a face validation during the modeling phase. Through interviews with aviation experts from the US Airforce, DHL, and Dnata, the structural assumptions of the model were inspected. The experts concluded that the assumptions are acceptable. However, the experts noted that our assumption of an intact airport infrastructural restricts the applicability of the model to cases where the airport is outside of the affected zone. Examples of such cases include the airports of Cebu and Manila in the response to Haiyan (Comes et al. 2015) or Balikpapan airport for the response to the 2018 Sulawesi tsunami and earthquake.
3. Internal validity: Several replications of the model were run to determine the internal variability in the model results (Sargent 2007). With 160 replications 95% of all model output values fall within an acceptable range of the mean output. The largest internal variability consists of the throughput time KPI of the aircraft unloading component. The largest internal variability was found in KPI_3 (throughput time) at the aircraft unloading component during. In Fig. 9 an overview of the validation runs is presented. In this figure the combined policy with the extra resources arriving 4 days after the disaster in the scenario blue scenario (30% loss of workforce and 30% loose boxes) is displayed. 95% of all model output values fall within an acceptable range of the mean output this makes the model internally valid. For further findings and analysis, we refer to the full model and all data, which are available publicly and openly (Feil 2018b).
4. Sensitivity analysis: For almost all input parameters, a small change in input produced only a small change in output.

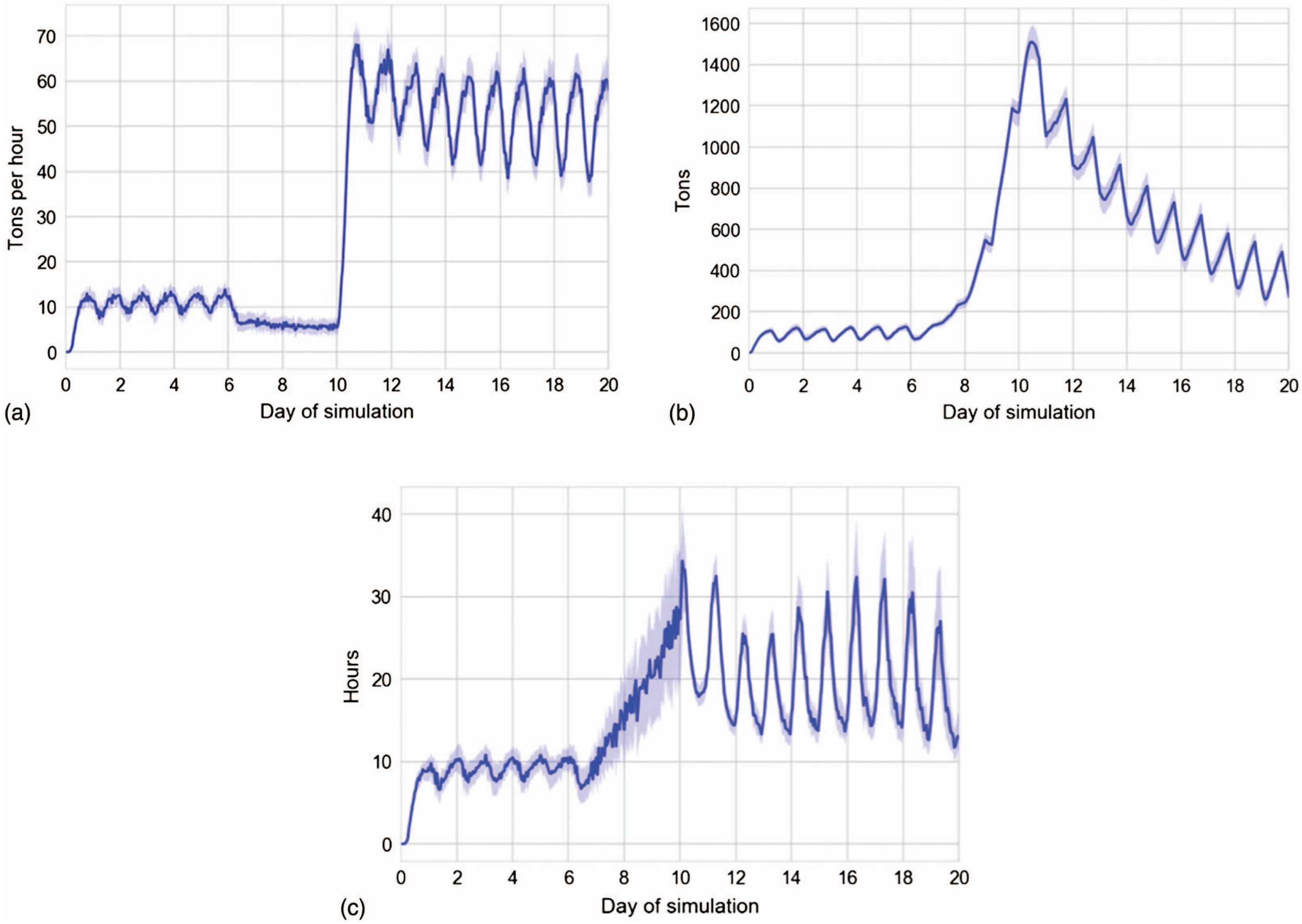

Fig. 9. (Color) Internal validity of combined policy with the extra resources arriving at the 10th day in the blue scenario (30% loss of workforce and 30 % share of loose boxes): (a) processed cargo; (b) idle cargo; and (c) throughput time.

One notable exception identified through the sensitivity analysis is the number of high lifters and the number of unloading workers. This is because in our model, one high lifter requires 8 unloading workers. If the number of unloading workers is decreased to 7 workers, the high lifter is not able to operate. According to our interviews, an aircraft can be unloaded with 7 workers, but requires substantial extra time. The disproportional influence on the number of cargo unit processed due to a small decrease in personnel is a limitation of the model, and policies that involve small changes in the number of workers should therefore not be tested in this model.

Overall, we can conclude that the model is validated, with the caveat of the sensitivity of small personnel changes for high lifter operations and the limitation of the model's scope to airports outside of the immediate disaster zone.

Conclusions

We started this paper with the introduction of a resilience framework that combines the notion of graceful extensibility (Woods 2015) with the need for rapid adaptation of the system itself. This adaptation leads to a new equilibrium or steady state of the critical infrastructure system. The resilience of the critical infrastructure can be measured by a triple resilience triangle based on its absorptive and adaptive capacity, and the rapidity of adaptation. Because rapid adaptation to changing required service levels during a disaster response is characteristic for airports, they provide an ideal study case to better understand the need to rapidly adapt and ramp up, which is also common for other critical hub infrastructures such as seaports, hospitals, or train stations.

To analyze the impact of resilience policies on a critical airport infrastructure under different scenarios, we next introduced a discrete event simulation model. This approach allowed us to gain insight in processes and problems within airports, and revealed the interdependency of system components and processes. We illustrated our approach through a stylized disaster case with six different policies intended to improve the level of resilience of the airport under four different disaster impact scenarios.

Our results showed first that not implementing any policies to handle the disaster leads to a certain collapse of the airport in view of the increased demands. Secondly, we found that distinct policies to improve the level of airport resilience impact multiple processes and KPIs simultaneously and differently. As such, an integrated approach to improve resilience is necessary. Third, our findings indicate that a decision-maker should implement a combination of different policies without delay. This includes in order of importance: (1) deploying extra resources, (2) setting up additional storage units, (3) creating extra holding capacity, and (4) implementing a prioritization policy on cargo type and aircraft size. With these consecutive policies, our findings suggested that the airport has the best chance to stay operational and provide the required surge capacity.

Many authors have stressed the need to incorporate learning into resilience for engineered systems (Woods et al. 2014; Mattsson and Jenelius 2015), organizational resilience (Vogus and Sutcliffe 2007), and disaster response (Comes et al. 2017). The findings in this paper hint at at least two important lessons for airport resilience. First, timing in the aftermath of a disaster is of the essence, and it is crucial that the airport immediately starts ramping up and increasing its capacity. In practice, this means that decision-makers should prepare the airport for a rapid scale-up of extra resources and extra holding and warehouse capacity. Second, in order to be able to swiftly implement these policies, the airport is dependent on its environment and other critical infrastructures. The successful implementation of airport resilience policies therefore also requires, for instance, to ensure that staff can reach the airport on time (e.g., by clearing roads or setting up transportation capacity), and that organizations comply to guidelines and standards for packing aircrafts by setting up, for example, training and awareness building activities. This also implies that stakeholders need to be involved in the construction and prioritization of scenarios (Thekdi and Lambert 2013).

Our model and analysis have several limitations that can be addressed in future work: first, we are focusing on the cargo system of an airport. The actual airport system also entails passenger flows and ground access (Malandri et al. 2017), which could be added to achieve a more comprehensive understanding of the airport system. Second, we assume that the airport infrastructure itself is not damaged. As such, our model is restricted to situations where the airport is serving as a hub into the affected areas. While damaged runways limit the number of incoming flights, the effect of destroyed warehouses and storage capacity will exacerbate the problem of congestion and material convergence.

Third, we focused here on the regime of the initial response phase, which lasts at most 14 days after the shock event (Styles 2017). Evidently, and as our results show, depending on the magnitude of disruption, and the capacity of the airport, it may not be possible to achieve adaptation within this timeframe. Yet, the 14 days time horizon of the initial response phase provides a useful frame for decision-makers, because this is the critical period of the response phase, within which the airport has to stabilize and adapt to serve the population in dire need. After the initial phase, typically flight schedules will change, and transport overland or via sea become more prominent. To further analyze this, we plan to expand the analysis to understand the resilience under regime changes (represented as the pressure by the patterns and cargo of incoming flights and availability of workers).

Fourth, as responders typically prioritize fast, but high-cost policies in the immediate response (Şahin et al. 2014), we focus here on the effectiveness of the policies in terms of achieving the required adaptation level. Our model can be extended with an analysis of economic efficiency. To this end, the cost of the individual measures needs to be compared with the economic impact of the delays. While in commercial setting, this impact can be relatively easily quantified [see, e.g., Janic (2009)], in a humanitarian setting, it has been suggested to use welfare economics principles to calculate deprivation cost (Holguín-Veras et al. 2013). To capture these phenomena, we aim to extend the airport resilience framework to include the wider supply chain network, both upstream (transportation from suppliers to the affected country; air bridges, etc.), and downstream (last-mile transportation to the affected areas and distribution to the beneficiaries), and determine appropriate deprivation cost functions.

Taken together, we strive to further develop this model-driven approach to resilience to the benefit of decision-makers at critical infrastructures who are facing the consequences of high-impact disaster events and have to fulfill an unexpected yet crucial support role in the life-saving response to these.

Data Availability Statement

The simulation model, scenario analyses, all data, and results are available in a public repository: Feil, Wouter (2018) Humanitarian airport model–data and analyses. 4TU.Centre for Research Data. Dataset. https://doi.org/10.4121/uuid:2fdf17f8-36c0-4d97-89cc-040c9a76e5ed.

References

Aldrich, D. P., and M. A. Meyer. 2015. "Social capital and community resilience." *Am. Behav. Sci.* 59 (2): 254–269. https://doi.org/10.1177/0002764214550299.

Aydin, N. Y., H. S. Duzgun, H. R. Heinimann, F. Wenzel, and K. R. Gnyawali. 2018. "Framework for improving the resilience and recovery of transportation networks under geohazard risks." *Int. J. Disaster Risk Reduct.* 31 (Oct): 832–843. https://doi.org/10.1016/j.ijdrr.2018.07.022.

Baharmand, H., T. Comes, and M. Lauras. 2017. "Managing in-country transportation risks in humanitarian supply chains by logistics service providers: Insights from the 2015 Nepal earthquake." *Int. J. Disaster Risk Reduct.* 24 (Sep): 549–559. https://doi.org/10.1016/j.ijdrr.2017.07.007.

Baharmand, H., T. Comes, and M. Lauras. 2019. "Bi-objective multi-layer location–allocation model for the immediate aftermath of sudden-onset disasters." *Transp. Res. Part E: Logist. Transp. Rev.* 127 (Jul): 86–110. https://doi.org/10.1016/j.tre.2019.05.002.

Ballestero, S. R. 2017. *Bulk vs. Cargo Loading System operations within the A320 Family.* Toulouse, France: Airbus S.A.S.

Barabadi, A., and Y. Z. Ayele. 2018. "Post-disaster infrastructure recovery: Prediction of recovery rate using historical data." *Reliab. Eng. Syst. Saf.* 169 (Jan): 209–223. https://doi.org/10.1016/j.ress.2017.08.018.

Bristow, D. N., and A. H. Hay. 2016. "Graph model for probabilistic resilience and recovery planning of multi-infrastructure systems." *J. Infrastruct. Syst.* 23 (3): 04016039. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000338.

Bruneau, M., S. E. Chang, R. T. Eguchi, G. C. Lee, T. D. O'Rourke, A. M. Reinhorn, M. Shinozuka, K. Tierney, W. A. Wallace, and D. Von Winterfeldt. 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.

Cardillo, A., M. Zanin, J. Gómez-Gardeñes, M. Romance, A. J. García del Amo, and S. Boccaletti. 2013. "Modeling the multi-layer nature of the european air transport network: Resilience and passengers rescheduling under random failures." *Eur. Phys. J. Spec. Top.* 215 (1): 23–33. https://doi.org/10.1140/epjst/e2013-01712-8.

Chen, L., and E. Miller-Hooks. 2012. "Resilience: an indicator of recovery capability in intermodal freight transport." *Transp. Sci.* 46 (1): 109–123. https://doi.org/10.1287/trsc.1110.0376.

Choi, J., N. Naderpajouh, D. J. Yu, and M. Hastak. 2019. "Capacity building for an infrastructure system in case of disaster using the system's associated social and technical components." *J. Manage. Eng.* 35 (4): 04019013. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000697.

Cimellaro, G. P., A. M. Reinhorn, and M. Bruneau. 2010. "Framework for analytical quantification of disaster resilience." *Eng. Struct.* 32 (11): 3639–3649. https://doi.org/10.1016/j.engstruct.2010.08.008.

Clark, K. L., U. Bhatia, E. A. Kodra, and A. R. Ganguly. 2018. "Resilience of the us national airspace system airport network." *IEEE Trans. Intell. Transp. Syst.* 19 (12): 3785–3794. https://doi.org/10.1109/TITS.2017.2784391.

Cochran, J. 2016. *Haiti port au prince international airport–Toussaint louverture*. Port au Prince, Haiti: Logistics Cluster.

Comes, T. 2016a. “Cognitive biases in humanitarian sensemaking and decision-making lessons from field research.” In *CogSIMA*, 56–62. New York: IEEE. https://doi.org/10.1109/COGSIMA.2016.7497786.

Comes, T. 2016b. “Designing for networked community resilience.” *Procedia Eng.* 159 (Jan): 6–11. https://doi.org/10.1016/j.proeng.2016.08.057.

Comes, T., and B. de Walle. 2014. “Measuring disaster resilience: The impact of hurricane Sandy on critical infrastructure systems.” *ISCRAM* 11 (May): 195–204.

Comes, T., K. Meesters, and S. Torjesen. 2017. “Making sense of crises: the implications of information asymmetries for resilience and social justice in disaster-ridden communities.” *Sustainable Resilient Infrastruct.* 4 (3): 1–13. https://doi.org/10.1080/23789689.2017.1405653.

Comes, T., O. Vybornova, and B. Van de Walle. 2015. “Bringing structure to the disaster data typhoon: An analysis of decision-makers’ information needs in the response to Haiyan.” In *Proc., 2015 AAAI Spring Symp. Series*. Palo Alto: Association for the Advancement of Artificial Intelligence.

Cook, A., H. A. Blom, F. Lillo, R. N. Mantegna, S. Micciche, D. Rivas, R. Vázquez, and M. Zanin. 2015. “Applying complexity science to air traffic management.” *J. Air Transp. Manage.* 42 (Jan): 149–158. https://doi.org/10.1016/j.jairtraman.2014.09.011.

De Neufville, R. 2016. “Airport systems planning and design.” In *Air transport management: An international perspective* 61–78. Milton Park, UK: Routledge.

Didier, M., M. Broccardo, S. Esposito, and B. Stojadinovic. 2018. “A compositional demand/supply framework to quantify the resilience of civil infrastructure systems (re-codes).” *Sustainable Resilient Infrastruct.* 3 (2): 86–102. https://doi.org/10.1080/23789689.2017.1364560.

D’Lima, M., and F. Medda. 2015. “A new measure of resilience: An application to the london underground.” *Transp. Res. Part A: Policy Pract.* 81 (Nov): 35–46. https://doi.org/10.1016/j.tra.2015.05.017.

Dunn, S., and S. M. Wilkinson. 2016. “Increasing the resilience of air traffic networks using a network graph theory approach.” *Transp. Res. Part E: Logist. Transp. Rev.* 90 (Jun): 39–50. https://doi.org/10.1016/j.tre.2015.09.011.

Elmqvist, T., E. Andersson, N. Frantzeskaki, T. McPhearson, P. Olsson, O. Gaffney, K. Takeuchi, and C. Folke. 2019. “Sustainability and resilience for transformation in the urban century.” *Nat. Sustainability* 2 (4): 267. https://doi.org/10.1038/s41893-019-0250-1.

Faturechi, R., E. Levenberg, and E. Miller-Hooks. 2014. “Evaluating and optimizing resilience of airport pavement networks.” *Comput. Oper. Res.* 43 (Mar): 335–348. https://doi.org/10.1016/j.cor.2013.10.009.

Feil, W. 2018a. *Humanitarian airport model–data and analyses*. Delft, Netherlands: 4Tu.Centre for Research Data.

Feil, W. 2018b. “Resilient airports.” Accessed June 1, 2019. https://repository.tudelft.nl/islandora/object/uuid%3A0b4c39d1-4ff3-4669-b4de-0e1167542cfe?collection=education.

Francis, R., and B. Bekera. 2014. “A metric and frameworks for resilience analysis of engineered and infrastructure systems.” *Reliab. Eng. Syst. Saf.* 121 (Jan): 90–103. https://doi.org/10.1016/j.ress.2013.07.004.

Hallegatte, S., J. Rentschler, and J. Rozenberg. 2019. *Lifelines: The resilient infrastructure opportunity.* Washington, DC: Worldbank.

Hanaika, S., Y. Indo, T. Hirata, T. Todorki, T. Aratani, and T. Osada. 2013. “Lessons and challenges in airport operation during a disaster.” *J. JSCE* 1 (1). 286–297. https://doi.org/10.2208/journalofjsce.1.1_286.

Heckmann, I., T. Comes, and S. Nickel. 2015. “A critical review on supply chain risk–definition, measure and modeling.” *Omega* 52 (Apr): 119–132. https://doi.org/10.1016/j.omega.2014.10.004.

Holguín-Veras, J., M. Jaller, L. N. Van Wassenhove, N. Pérez, and T. Wachtendorf. 2012. “Material convergence: Important and understudied disaster phenomenon.” *Nat. Hazards Rev.* 15 (1): 1–12. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000113.

Holguín-Veras, J., N. Pérez, M. Jaller, L. N. Van Wassenhove, and F. Aros-Vera. 2013. “On the appropriate objective function for post-disaster humanitarian logistics models.” *J. Oper. Manage.* 31 (5): 262–280. https://doi.org/10.1016/j.jom.2013.06.002.

Holguín-Veras, J., N. Pérez, S. Ukkusuri, T. Wachtendorf, and B. Brown. 2007. “Emergency logistics issues affecting the response to katrina: a synthesis and preliminary suggestions for improvement.” *Transp. Res. Rec.* 2022 (1): 76–82. https://doi.org/10.3141/2022-09.

Holguín-Veras, J., E. Taniguchi, M. Jaller, F. Aros-Vera, F. Ferreira, and R. G. Thompson. 2014. “The tohoku disasters: Chief lessons concerning the post disaster humanitarian logistics response and policy implications.” *Transp. Res. Part A: Policy Pract.* 69 (Nov): 86–104. https://doi.org/10.1016/j.tra.2014.08.003.

Holling, C. S. 1973. “Resilience and stability of ecological systems.” *Annual Rev. Ecol. Syst.* 4 (1): 1–23. https://doi.org/10.1146/annurev.es.04.110173.000245.

Hosseini, S., K. Barker, and J. E. Ramirez-Marquez. 2016. “A review of definitions and measures of system resilience.” *Reliab. Eng. Syst. Saf.* 145 (Jan): 47–61. https://doi.org/10.1016/j.ress.2015.08.006.

Ilbeigi, M., and B. Dilkina. 2018. “Statistical approach to quantifying the destructive impact of natural disasters on petroleum infrastructures.” *J. Manage. Eng.* 34 (1): 04017042. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000566.

Janic, M. 2009. “Concept for prioritizing aircraft operations at congested airports.” *Transp. Res. Rec.* 2106 (1): 100–108. https://doi.org/10.3141/2106-12.

Janić, M. 2015. “Modelling the resilience, friability and costs of an air transport network affected by a large-scale disruptive event.” *Transp. Res. Part A* 81 (Nov): 77–92. https://doi.org/10.1016/j.tra.2015.07.012.

Jordan, R., M. Ishutkina, and T. Reynolds. 2010. “A statistical learning approach to the modeling of aircraft taxi time.” In *Proc., Digital Avionics Systems Conference (DASC)*. New York: IEEE.

Joustra, P., and N. Van Dijk. 2001. “Simulation of check-in at airports.” In *Proc., 2001 Winter Simulation Conf.*, 1023–1028. New York: IEEE.

Kallen, N. A. 2015. “Multi-perspective design fast-track facility cargo transhipment amsterdam airport Schiphol.” Ph.D. thesis, Aerospace Engineering, TU Delft.

Logistics Cluster. 2010. *Situation report Haiti 18-01-10*. Rep. No. 1. Rome, Italy: Logistics Cluster.

Logistics Cluster. 2015. *Nepal earthquake situation update*. Rome, Italy: Logistics Cluster.

Lordan, O., J. M. Sallan, P. Simo, and D. Gonzalez-Prieto. 2014. “Robustness of the air transport network.” *Transp. Res. Part E: Logis. Transp. Rev.* 68 (Aug): 155–163. https://doi.org/10.1016/j.tre.2014.05.011.

Lou, Y., and L. Zhang. 2011. “Defending transportation networks against random and targeted attacks.” *Transp. Res. Rec.* 2234 (1): 31–40. https://doi.org/10.3141/2234-04.

Malandri, C., L. Mantecchini, and M. N. Postorino. 2017. “Airport ground access reliability and resilience of transit networks: a case study.” *Transp. Res. Procedia* 27 (Jan): 1129–1136. https://doi.org/10.1016/j.trpro.2017.12.022.

Manataki, I. E., and K. G. Zografos. 2009. “A generic system dynamics based tool for airport terminal performance analysis.” *Transp. Res. Part C* 17 (4): 428–443. https://doi.org/10.1016/j.trc.2009.02.001.

Manataki, I. E., and K. G. Zografos. 2010. “Assessing airport terminal performance using a system dynamics model.” *J. Air Transp Manage.* 16 (2): 86–93. https://doi.org/10.1016/j.jairtraman.2009.10.007.

Mattsson, L.-G., and E. Jenelius. 2015. “Vulnerability and resilience of transport systems–a discussion of recent research.” *Transp. Res. Part A* 81 (Nov): 16–34. https://doi.org/10.1016/j.tra.2015.06.002.

Meerow, S., J. P. Newell, and M. Stults. 2016. “Defining urban resilience: A review.” *Landscape Urban Plann.* 147 (Mar): 38–49. https://doi.org/10.1016/j.landurbplan.2015.11.011.

Memarzadeh, M., and M. Pozzi. 2019. “Model-free reinforcement learning with model-based safe exploration: Optimizing adaptive recovery process of infrastructure systems.” *Struct. Saf.* 80 (Sep): 46–55. https://doi.org/10.1016/j.strusafe.2019.04.003.

Miller-Hooks, E., X. Zhang, and R. Faturechi. 2012. “Measuring and maximizing resilience of freight transportation networks.” *Comput. Oper. Res.* 39 (7): 1633–1643. https://doi.org/10.1016/j.cor.2011.09.017.

Neudert, E. 2010. “Involvement and integration of commercial airlines in disaster relief operation.” Ph.D. thesis, School of Management, Cranfiel Univ.

Nozhati, S., Y. Sarkale, B. Ellingwood, E. K. Chong, and H. Mahmoud. 2019. “Near-optimal planning using approximate dynamic programming to enhance post-hazard community resilience management." *Reliab. Eng. Syst. Saf.* 181 (Jan): 116–126. https://doi.org/10.1016/j.ress.2018.09.011.

Nsakanda, A., M. Turcotte, and M. Diaby. 2004. "Air cargo operations evaluation and analysis through simulation." In *Proc., 2004 Winter Simulation Conf.*, 711–719. New York: IEEE.

Rose, A. 2007. "Economic resilience to natural and man-made disasters: Multidisciplinary origins and contextual dimensions." *Environ. Hazards* 7 (4): 383–398. https://doi.org/10.1016/j.envhaz.2007.10.001.

Şahin, A., M. Alp Ertem, and E. Emür. 2014. "Using containers as storage facilities in humanitarian logistics." *J. Humanitarian Logist. Supply Chain Manage.* 4 (2): 286–307. https://doi.org/10.1108/JHLSCM-08-2013-0029.

Sargent, R. G. 2007. "Verification and validation of simulation models." In *Proc., 2007 Winter Simulation Conf.*, 124–137. New York: IEEE.

Schoenmaker, M. 2016. "Increasing air cargo throughput per ground surface unit under footprint constraints." Ph.D. thesis, Aerospace Engineering, TU Delft.

Schuppener, K. M. 2016. "Design of the input and output cargo flows for a Fast-Track at Amsterdam airport Schiphol." Ph.D. thesis, Aerospace Engineering, TU Delft.

Sherali, H. D., E. Dalkiran, and T. S. Glickman. 2011. "Selecting optimal alternatives and risk reduction strategies in decision trees." *Oper. Res.* 59 (3): 631–647. https://doi.org/10.1287/opre.1110.0923.

Stanhope, A. 2010. *Logistics cluster Haiti consolidated situation report*. Rome: Logistics Cluster.

Styles, L. 2017. "What is the LOG?" Accessed June 1, 2019. http://dlca.logcluster.org/display/public/LOG/Introduction.

Thekdi, S. A., and J. H. Lambert. 2013. "Quantification of scenarios and stakeholders influencing priorities for risk mitigation in infrastructure systems." *J. Manage. Eng.* 30 (1): 32–40. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000170.

Turnquist, M., and E. Vugrin. 2013. "Design for resilience in infrastructure distribution networks." *Environ. Syst. Decis.* 33 (1): 104–120. https://doi.org/10.1007/s10669-012-9428-z.

Turoff, M., M. Chumer, B. V. de Walle, and X. Yao. 2004. "The design of a dynamic emergency response management information system (dermis)." *J. Inf. Technol. Theory Appl.* 5 (4): 1–35.

Veatch, M., and J. Goentzel. 2018. "Feeding the bottleneck: airport congestion during relief operations." *J. Humanitarian Logist. Supply Chain Manage.* 8 (4): 430–446. https://doi.org/10.1108/JHLSCM-01-2018-0006.

Verbraeck, A., and E. Valentin. 2002. "Simulation building blocks for airport terminal modeling." In *Proc., 2002 Winter Simulation Conf.*, 1199–1206. New York: IEEE.

Vogus, T., and K. Sutcliffe. 2007. "Organizational resilience: Twards a theory and research agenda." In *Proc., 2007 IEEE Conf. on Systems, Man and Cybernetics*, 3418–3422. New York: IEEE.

Woods, D., Y. Chan, and J. Wreathall. 2014. "The stress–strain model of resilience operationalizes the four cornerstones of resilience engineering." In *Proc., 5th Resilience Engineering Symp.*, 17–22. Paris: Resilience Engineering Association.

Woods, D. D. 2015. "Four concepts for resilience and the implications for the future of resilience engineering." *Reliab. Eng. Syst. Saf.* 141 (Sep): 5–9. https://doi.org/10.1016/j.ress.2015.03.018.

Zio, E. 2016. "Challenges in the vulnerability and risk analysis of critical infrastructures." *Reliab. Eng. Syst. Saf.* 152 (Aug): 137–150. https://doi.org/10.1016/j.ress.2016.02.009.

Zobel, C. W. 2011. "Representing perceived tradeoffs in defining disaster resilience." *Decis. Support Syst.* 50 (2): 394–403. https://doi.org/10.1016/j.dss.2010.10.001.